



NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

**NATIONS AT RISK—INDICATORS OF FRAGILITY IN
STATES SUSCEPTIBLE TO TERRORIST ATTACKS**

by

Fabian U. Kuessner

March 2018

Thesis Advisor:
Co-Advisor

Ryan Sullivan
Ryan Garcia

Approved for public release. Distribution is unlimited.

THIS PAGE INTENTIONALLY LEFT BLANK

REPORT DOCUMENTATION PAGE			<i>Form Approved OMB No. 0704-0188</i>	
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington, DC 20503.				
1. AGENCY USE ONLY (Leave blank)		2. REPORT DATE March 2018		3. REPORT TYPE AND DATES COVERED Master's thesis
4. TITLE AND SUBTITLE NATIONS AT RISK—INDICATORS OF FRAGILITY IN STATES SUSCEPTIBLE TO TERRORIST ATTACKS				5. FUNDING NUMBERS
6. AUTHOR(S) Fabian U. Kuessner				
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000				8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING /MONITORING AGENCY NAME(S) AND ADDRESS(ES) N/A				10. SPONSORING / MONITORING AGENCY REPORT NUMBER
11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government. IRB number _____. N/A.				
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release. Distribution is unlimited.				12b. DISTRIBUTION CODE
13. ABSTRACT (maximum 200 words) Using cross-national data from 2006–2016 and 174 states, this thesis details an investigation of the relationship between state fragility and the incidence of terrorism. The approach is threefold. The first step adapts the most common methodology from the literature, the negative binomial regression model, to reproduce existing outcomes by taking advantage of today's availability of broader data. However, as terrorism is endogenous to state fragility, I use the Arellano-Bond Estimator in the second step to overcome the reverse causality bias in this fragility-terrorism-nexus. The last step, a comparison of the outcomes of my two methodologies, finds the problems arising from this reverse causality bias are too substantial to use negative binomial regression as an appropriate model to derive strategies for policy makers. Moreover, the outcomes show that economic inequality and factionalization along ethnic and religious lines are root causes for terrorism, and that terrorism itself leads to more terrorism in the future. Additionally, my research finds that the influx of refugees has no impact on the occurrence of terrorism in the short term. However, subject to a society's capacity to assimilate groups, migration flows can have implications for the occurrence of terrorism over time.				
14. SUBJECT TERMS terror, terrorism, terrorist, terrorist attacks, incident, fragility, state fragility, failed states, failing states, state failure, resilience, indicators, causality, causal, determinants, factionalization, economic inequality,				15. NUMBER OF PAGES 95
				16. PRICE CODE
17. SECURITY CLASSIFICATION OF REPORT Unclassified		18. SECURITY CLASSIFICATION OF THIS PAGE Unclassified		19. SECURITY CLASSIFICATION OF ABSTRACT Unclassified
				20. LIMITATION OF ABSTRACT UU

THIS PAGE INTENTIONALLY LEFT BLANK

Approved for public release. Distribution is unlimited.

**NATIONS AT RISK—INDICATORS OF FRAGILITY IN STATES
SUSCEPTIBLE TO TERRORIST ATTACKS**

Fabian U. Kuessner
Commander, German Navy
Dipl. Kaufmann, Universität der Bundeswehr München, 2004

Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN MANAGEMENT

from the

**NAVAL POSTGRADUATE SCHOOL
March 2018**

Approved by: Ryan Sullivan
Thesis Advisor

Ryan Garcia
Co-Advisor

Yu-Chu Shen
Academic Associate
Graduate School of Business and Public Policy

THIS PAGE INTENTIONALLY LEFT BLANK

ABSTRACT

Using cross-national data from 2006–2016 and 174 states, this thesis details an investigation of the relationship between state fragility and the incidence of terrorism. The approach is threefold.

The first step adapts the most common methodology from the literature, the negative binomial regression model, to reproduce existing outcomes by taking advantage of today's availability of broader data. However, as terrorism is endogenous to state fragility, I use the Arellano-Bond Estimator in the second step to overcome the reverse causality bias in this fragility-terrorism-nexus.

The last step, a comparison of the outcomes of my two methodologies, finds the problems arising from this reverse causality bias are too substantial to use negative binomial regression as an appropriate model to derive strategies for policy makers.

Moreover, the outcomes show that economic inequality and factionalization along ethnic and religious lines are root causes for terrorism, and that terrorism itself leads to more terrorism in the future. Additionally, my research finds that the influx of refugees has no impact on the occurrence of terrorism in the short term. However, subject to a society's capacity to assimilate groups, migration flows can have implications for the occurrence of terrorism over time.

THIS PAGE INTENTIONALLY LEFT BLANK

TABLE OF CONTENTS

I.	INTRODUCTION.....	1
II.	LITERATURE REVIEW	7
III.	DATA AND CODING OF THE VARIABLES	13
A.	THE GLOBAL TERRORIST DATABASE.....	13
B.	THE FRAGILE STATES INDEX.....	14
C.	COMPILED DATABASE.....	16
1.	Dependent Variables	16
2.	Independent Variables	19
3.	Evaluation of the Data	23
IV.	METHODOLOGY.....	27
A.	INTRODUCTION OF THE DIFFERENT MODELS.....	29
1.	The Negative Binomial Regression Models.....	29
2.	Finding Causality with the Arellano-Bond Estimator	31
V.	RESULTS	37
A.	RESULTS FROM THE NEGATIVE BINOMIAL REGRESSION MODELS	37
1.	Model 1: Number of Terrorist Attacks and State Fragility.....	37
2.	Model 2: Raw Data Analysis—Number of Terrorist Attacks and State Fragility.....	38
3.	Model 3: Number of Terrorist Attacks and Indicators of State Fragility.....	39
4.	Model 4: Best Fitted Model—Number of Terrorist Attacks and Indicators of State Fragility	41
5.	Discussion of the Results of the NBR Models	42
B.	RESULTS FROM THE ARELLANO BOND ESTIMATOR MODELS	43
1.	Model 5: Number of Terrorist Attacks and State Fragility (Arellano-Bond Estimator)	44
2.	Model 6: Raw Data Analysis—Number of Terrorist Attacks and State Fragility (Arellano-Bond Estimator).....	45

3.	Model 7.1: Best Fitted Model—Number of Terrorist Attacks and State Fragility (Arellano-Bond Estimator)	46
4.	Model 7.2: Best Fitted Model—Logged Total Monetary Value and State Fragility (Arellano-Bond Estimator)	52
5.	Model 7.3: Best Fitted Model—Total Number of Fatalities and State Fragility (Arellano-Bond Estimator)	54
C.	COMPARING THE RESULTS FROM THE DIFFERENT MODELS	55
VI.	CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH	59
A.	CONCLUSIONS	59
B.	RECOMMENDATIONS FOR FUTURE RESEARCH	63
	APPENDIX A. LIST OF SUB-INDICATORS IN THE FSI	65
	APPENDIX B. MODEL 2: RAW DATA ANALYSIS—NUMBER OF TERRORIST ATTACKS AND STATE FRAGILITY	67
	APPENDIX C. MODEL 6: RAW DATA ANALYSIS—NUMBER OF TERRORIST ATTACKS AND STATE FRAGILITY (ARELLANO-BOND ESTIMATOR)	69
	LIST OF REFERENCES	71
	INITIAL DISTRIBUTION LIST	77

LIST OF FIGURES

Figure 1.	Fatality and Number of Terrorist Attacks	1
-----------	--	---

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF TABLES

Table 1.	Model 1.....	37
Table 2.	Model 3.....	40
Table 3.	Model 4.....	41
Table 4.	Model 5.....	44
Table 5.	Model 7.1.....	47
Table 6.	Model 7.2.....	53
Table 7.	Model 7.3.....	54

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF ACRONYMS AND ABBREVIATIONS

AIC	Akaike information criterion
BIC	Bayesian information criterion
CAST	Conflict Assessment System Tool
DNI	Director of National Intelligence
FE	fixed effects
FFP	Fund for Peace
FSI	Fragile States Index
GDP	gross domestic product
GDT	Global Terrorist Database
GMM	generalized method of moments
HDI	human development index
IDP	internally displaced people
IRR	incident rate ratio
IV	instrumental variable
MAIS	relative disutility factors by injury severity level
NBR	negative binomial regression
NGO	non-governmental organization
NSS	national security strategy
NVP	net present value
POTUS	President of the United States of America
START	National Consortium for the Study of Terrorism and Responses to Terrorism
UN	United Nations
VSL	value of a statistical life

THIS PAGE INTENTIONALLY LEFT BLANK

ACKNOWLEDGMENTS

First, I want to acknowledge all of the professors within the Manpower System Analysis curriculum at the Naval Postgraduate School for providing me with an exceptional educational experience.

I want to give special thanks to Professor Ryan Sullivan and Professor Ryan Garcia, whose direction and expertise significantly contributed to the successful completion of my thesis. I would be remiss if I did not thank Professor Marigee Bacolod and Professor Sae Young (Tom) Ahn for their advice and inspiring comments, which helped develop my work.

Most importantly, I want to express my sincere gratitude to my wife, Lonneke, for her love, patience, and endless support. During our two-year stay in California, you gave me the most precious gift imaginable—our beautiful daughter Marlijn. To my daughter, thank you for joining our family and making our time here in California perfect. Your curiosity and sense of wonder is so inspiring to me. Helping your mom care for you was not always conducive to completing graduate-level academic work; however, seeing you grow before my eyes was more than worth the effort.

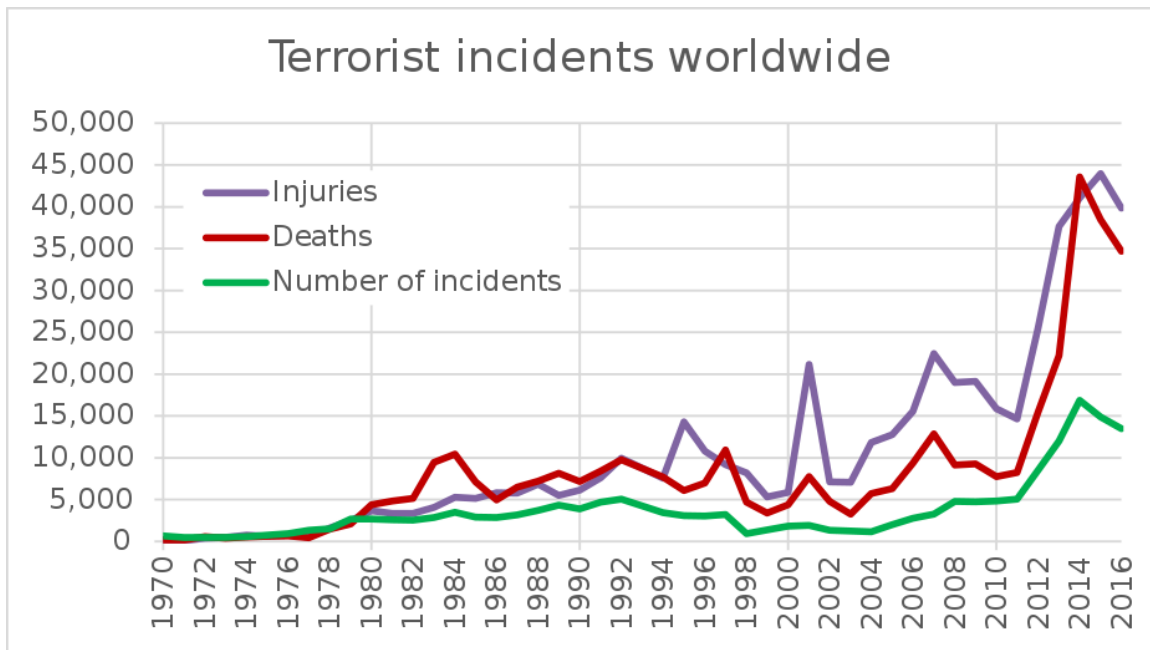
Moreover, I would like to thank our friends and families back in Germany and the Netherlands for their unwavering support and help. Lonneke, Marlijn, and I look forward to reuniting with you in the near future.

I dedicate this thesis to my father-in-law, Hendrik Willem van Dijk, who unexpectedly passed away on 26 February 2018. Rest in peace, Henk.

THIS PAGE INTENTIONALLY LEFT BLANK

I. INTRODUCTION

Since the terrorist attacks of 9/11, the phenomenon of terror weighs heavily on the populace and makes headlines every day. This subjective perception of a growing prevalence of terror is fueled by a trend that expresses in an increased frequency of terrorist attacks and a growing number of fatalities caused by terrorism since the 1970s, as shown in Figure 1.



Data for this graphic were accessed from Global Terrorism Database (2017).

Figure 1. Fatality and Number of Terrorist Attacks

From a long-term perspective, however, this trend does not express a sustainable and constant increase. Rather, it reveals an unsteady pattern with peaks in the early 1980s and in the mid-1990s, followed by a decline until 2001. Then again, after the dramatic terrorist attacks of 9/11, the numbers of fatalities and terrorist attacks were on the rise. Since 2011, the trend has developed even more momentum, as can be observed in the chart with its exponential progression.

Regardless of whether these attacks in 2001 are considered a caesura in global history, the phenomenon of terror can be traced back in history and is a highly relevant topic. Subject to the numerous definitions of terrorism, we find terroristic violence as a means to gain power over others in the Roman Empire, in medieval times by a group of individuals called the Assassins, in the reign of terror at the time of the French Revolution, and in the dictatorships of the 20th century. The purpose of terror is manifold as it pursues different political, ideological, religious, economic, or social objectives. Based on its motivation and capabilities, terrorism targets governments, civilians, religions, infrastructure, tourists, and private property and uses diverse tactics and means of different scale to achieve its goals.

This complex nature of terrorism makes it challenging, if not impossible, for governments to anticipate terrorist attacks. In an attempt to recognize patterns of terrorist activities, the research on terrorism grew rapidly in the aftermath of 9/11. In one study, Sandler identifies five key areas of this research, the “analyses of terrorist attack trends, the economic consequences of terrorism, the study of counterterrorism effectiveness, the causes of terrorism, and the relationship of terrorism and liberal democracies” (Sandler, 2014, p. 257). Furthermore, there is an increase of advanced econometric analyses (Security Economics) to identify and quantify determinants of terror. Alan B. Krueger, former Chairman of President Obama’s Council of Economic Advisers, approaches the phenomenon of terrorism with a systematic data-driven research. His well-recognized study debunks the popular assumption that poverty and poor education cause terrorism but reveals that “terrorism occurs within a social context” (Krueger, 2007, p. 6). Other studies have found that terrorism follows statistical patterns and provide empirical evidence that relates terrorism to socio-economic and political underdevelopment, as well as demographic and institutional factors (Krieger & Meierrieks 2011). Nevertheless, these attempts to identify determinants of terror do not remain undisputed as they treat terror predominantly homogeneously. In a discussion paper, Kis-Katos, Liebert, and Schulze (2012) allege that “the existing literature on

the determinants of terrorism treats terror as a uniform phenomenon” (p. 1) and thus challenge a too one-sided reflection. The authors develop a contextual approach to

show that terror originates more often from richer and more urbanized countries and that economic growth and better infrastructure reduce terror levels. Moreover, [...] democracy is unrelated to terror, except that terror originates significantly less from the most undemocratic states. Terror is rooted in unstable and conflict-ridden states and is strongly persistent. (Kis-Katos et al., 2012, p. 29)

The discussion about the origins of terror is often tied to a state’s relative stability or its opposite, fragility. In the aftermath of 9/11, national security documents have described failed states to “[...] offer terrorists [...] safe haven and possible access to weapons of mass destruction” (Director of National Intelligence [DNI], 2009, p. 4). Even the most recent National Security Strategy (NSS) of the United States of America, references the significant security concerns that are associated with weak or failing states (President of the United States of America [POTUS], 2017).

In a pioneering effort to analyze the relationship of state fragility and terrorism empirically, Piazza (2008) finds that "states experiencing intense state failures are statistically more likely to be the target of attacks and are more likely to have their nationals commit attacks overseas" (p.481). Furthermore, he finds that “the relationship between intensity and pervasiveness of state failure and transnational terrorism is linear” (Piazza, 2008, p. 483). Piazza justifies his findings based on the RAND Database of Worldwide Terrorism Incidents with a sample of 2,632 observations from 2000 to 2006. By merging this data with the Fragile States Index (FSI) for the year 2006, he uses cross-sectional data for his analysis. Although methodologically sound, this approach leads to a bigger measurement error as he links the fragility value of the year 2006 to all the observations from 2000 to 2006, which implies biased results. Knowing about some shortcomings of his initial approach, Piazza concedes that his study requires replication.

This thesis adopts Piazza's idea to investigate the relationship of state fragility and the incidence of terror. It takes advantage of the broader data currently available by using panel data of the FSI from 2006 to 2016, merged with the data of the Global Terrorism Database (GTD) (Fund for Peace, 2017; University of Maryland, 2017). If evidence reveals that certain indicators of state fragility are positively correlated with the number of terrorist attacks, these results would provide a foundation for recognizing state at-risk characteristics and help to develop recommendations for policies and programs.

Using cross-national data from 2006 to 2016 and 174 states, I use a threefold approach to conduct my analysis. The first step is to adapt the most common methodology from the literature, the negative binomial regression model, to reproduce existing outcomes. However, as terrorism is endogenous to state fragility, the second step uses the Arellano-Bond Estimator to overcome the reverse causality bias in this fragility-terrorism nexus. Finally, outcomes of the two methodologies reveals that the problems arising from this reverse causality bias are substantial, rendering the negative binomial regression an inappropriate model to derive strategies for policy makers. Moreover, the findings indicate that economic inequality and factionalization along ethnic and religious lines are root causes for terrorism and provide robust evidence that a terrorist attack today entails further terrorist attacks in the future. Thus, I show that the phenomenon of terrorism follows a self-sustaining mechanism. A further result shows that the influx of refugees has no impact on the occurrence of terrorism in the short term. Nevertheless, subject to a society's capacity to assimilate groups, migrations flows can have implications in the long term, as they can increase the factionalization of a country and eventually lead to a heightened perception of inequality.

The thesis proceeds as follows. Chapter II contains a literature review and gives an overview of the broad spectrum of results in previous research on the determinants of terrorism. Chapter III introduces and discusses the data and variables for the current analysis and presents different ways to operationalize terrorism. In Chapter IV, I describe my methodology and present my different

econometric models to reproduce results of other scholars as a first step. Then, a discussion of the outcomes serves as the next step, which eventually introduces a different methodology to address an endogeneity issue I identified. Chapter V presents my own results. In Chapter VI, I draw my conclusions, derive implications for policies, and furthermore give recommendations for future research.

THIS PAGE INTENTIONALLY LEFT BLANK

II. LITERATURE REVIEW

One of the main characteristics of terrorism is its surprising momentum and, at first glance, its inconsistent pattern, which makes predicting when and where terrorists will strike next difficult (Lawson & Stedmon, 2015). In addition to that, the uncertainty associated with terror is an intended byproduct in a terrorist's strategy bringing with it serious psychological implications (Johnson, 1982). This intangible nature of terror, combined with the phenomenon of suicide attacks, might cause someone to presume that terrorists act irrationally, as though they value their principles and beliefs over their own life. Conversely, several scholars have attributed rationality to terrorists' acts. Whereas Pape differentiates between those irrational or fanatical suicide terrorists and their leaders, who are more in a managerial role of pursuing an agenda of resistance and coercion (Pape, 2017), other researchers conclude that "the level of terrorism we observe is consistent with almost everyone being close to homo economicus, especially if we think in terms of the selfish gene rather than the selfish individual" (Caplan, 2006, p. 105). Either way, it is worth addressing the issue of the terrorists' rationales to determine any patterns exist that would enable us to predict or derive the future behavior of terrorists.

In an attempt to recognize patterns of terrorist activities, the research on terrorism grew rapidly in the aftermath of 9/11. In "an eclectic review of the analytical study of terrorism that views all agents as rational decision-makers" Sandler identifies five key areas of research that focus on the phenomenon and consequences of terrorism, namely the "analyses of terrorist attack trends, the economic consequences of terrorism, the study of counterterrorism effectiveness, the causes of terrorism, and the relationship of terrorism and liberal democracies" (Sandler, 2014, p. 257). Moreover, there is an increase in advanced econometric analyses to identify and quantify determinants of terror. These research papers "doing analytical work on terrorism have converged to a common definition of terrorism in keeping with the primary terrorist event databases" (Sandler, 2013, p.

768). Based on this collective understanding of terrorism, scholars have approached the phenomenon of terrorism with systematic data-driven research attempting to identify the determinants of terror. These studies provide empirical evidence that terrorism follows statistical patterns that relate terrorism to economic deprivation, political underdevelopment, socio-economic factors, demographic tensions, and religious and ethnic inequalities (Llussá & Tavares, 2007; Krieger et al., 2011; Meierrieks & Krieger, 2013).

Attempts to explain the causes of terrorism with respect to economic deprivation, trace back in history. Gurr (1970) hypothesized that “the potential for collective violence varies strongly with the intensity and scope of relative deprivation” (p. 360) and justifies his idea with the frustration-aggression mechanism of the human. He argues that the divergence between an individual’s expected income and his actual earnings is a catalyst for violent acts. This relationship matters for countries with a profile of significant economic inequality, as frustrated individuals might exhibit a lower inhibition threshold to carry out terrorist attacks. However, Gurr’s model remains simplistic as it does not consider any other influences such as political dysfunction or socio-economic factors.

In fact, research including more variables than just economic deprivation similarly found this positive relationship between economic inequality and the increased incidence of terrorist attacks (Freytag, Krueger, Meierrieks, & Schneider, 2011). In addition to Gurr’s one-dimensional analysis, these models also controlled for socio-economic factors, level of education, unemployment, and poverty. The authors reveal that economic deprivation and poor socio-economic conditions are strongly associated with a higher rate of terrorist activity and justify their results with the economic principle of opportunity costs. Thus, the tradeoff between pursuing regular employment or engaging in terrorist activities characterizes one determinant of terrorism, as a rational actor’s decisions are influenced by reasonable cost-benefit considerations. Moreover, the authors conclude that terrorism is “predominantly rooted in unfavorable political and demographic conditions” (Freytag et al., 2011, p. 16). The same positive

relationship between terrorism and economic deprivation, measured by inequality, unemployment, lack of education, and factionalization along ethnic and religious lines, was discovered by George, and Caruso and Schneider (George, 2016; Caruso & Schneider 2013). In contrast to these findings, other scholars found only little evidence for this association. Krueger included further control variables in his model and found that “lack of education and income are not important root causes for terrorism”; however, “they can be part of the solution” (Krueger, 2007, p.51). According to Krieger and Meierrieks (2011), “there is only limited evidence to support the hypothesis that economic deprivation causes terrorism” (p. 10). They find instead that this relationship gets more insignificant “once it is controlled for institutional and political factors” (Krieger & Meierrieks, 2011, p. 10).

Another controversially discussed determinant of terrorism is the relationship between terrorism and the number of refugees in a country. Whereas Choi and Salehyan (2013) find evidence that “countries with many refugees are more likely to experience both domestic and international terrorism” (p. 53), Randahl (2016) concludes that his “results clearly give no support at all for the hypothesis that refugees would cause an increase in either the incidence or magnitude of terrorism in their host countries” (p. 51).

With respect to diverse societies, scholars found that factionalization along ethnic and religious lines can foster terrorism, too (Gassebner & Luechinger, 2011). Blomberg, Gaibullov, and Sandler (2011) show that terrorist organizations are “bolstered by democratic institutions and an intermediate level of ethnic factionalization at home” (p. 441). They provide good arguments for their results by stating that heterogeneous societies have a higher capacity to assimilate groups whereas more homogeneous societies are simply more intolerant of terrorist activities and therefore actively counter insurgents more deliberately. Other studies also found evidence of this positive relationship between terrorism and the degree of factionalization (Kis-Katos et al., 2012; Schulz, 2015). However, as Mascarenhas and Sandler (2014) show, a linguistic factionalization is not significantly related to terrorism.

Another determinant of terrorism relates to the political order of a nation-state. In his qualitative analysis Johnson (1982) showed that the stability of social organization requires coercive power imposed by a governmental authority. A lack thereof implies a reasonable risk of violence and “since violence is both the negation of, and a possibility in, all social systems, sociologists regard it as one of the major criteria for defining a social system and for evaluating the degree of the system’s stability” (p.10). Correspondingly, policy makers and scholars have pointed to significant security concerns associated with weak or failing states (POTUS, 2017; Hagel, 2004; Newman, 2007; Rice, 2006; George, 2016). Interestingly, Hehir (2007) found that “there is no causal link or pronounced correlation ... between democratization and the negation of terrorism” as an indicator; rather the legitimate coercive power of governance, not the particular type of a political system, determines the level of terrorism (p. 328). Whereas Johnson performs no statistical tests on his study of the relationship between fragility and the incidence of terror, there are only few quantitative analyses investigating this nexus (Piazza, 2008; Tikuisis, 2009; Okafor & Piesse, 2017). As already stated in the previous chapter, Piazza finds statistical evidence that unstable countries are significantly more susceptible to terrorist attacks and moreover are incubators of terror (Piazza, 2008). His results might be misleading, however, because terrorism is endogenous to his measure of state failure, and he did not address this reverse causality bias, as fragility might lead to terrorism, which consequently destabilizes a country. Okafor and Piesse (2017) found the same relationship; however, they base their findings on a dataset with little statistical power as they restrict their data to a sample of those 38 countries in the top category of the FSI, and thus are all considered to be fragile. “Generally though, there are too few analyses of failure’s potential relationship to terrorism to make any definitive claims” concludes Coggins (Coggins, 2015, p. 458).

This review of the broad and sometimes incoherent literature illustrates the range of results. “However fruitful, the diversity of terrorism research was not accompanied by any substantial increase in cross-fertilization between themes

and methodologies” conclude Llussá and Tavares (2011, p. 105–106) in their portrait of the existing knowledge on the economics of terrorism. Their argument finds further support by Kis-Katos et al. (2012), who noticed a “standard model in the empirical analysis of terrorism” (p. 13). As a result of this homogeneity, Llussá and Tavares (2011) documented an “almost schizophrenic” (p. 113) imbalance between empirical and theoretical methods and derived a “latent demand for either empirical validation of existing concepts, or formalization of empirical regularities” (p. 113). Despite the marked similarity of the approaches and methodologies in the documented research, the variety of outcomes is surprising, and some results are even highly contradictory. A reason for this can be a detail that all the cited studies have in common; they neither acknowledge nor address the problem of a reverse causality bias in the research field of finding determinants of terror, although terrorism is often endogenous to their numerous determinants of terror. In general, only a few scholars have addressed these implications of a reverse causality bias in their attempts to identify predictors of terrorism (Kang & Lee, 2005; Meierrieks & Gries, 2013; Krieger & Meierrieks, 2015).

With respect to the described gaps in literature, I adopt Piazza’s idea to investigate the relationship of state fragility and the incidence of terror. This study takes advantage of the broader data available today by using panel data of the FSI from 2006 to 2016, merged with the data of the GTD (Fund for Peace, 2017; University of Maryland, 2017). Furthermore, I address the issue of endogeneity in this nexus and introduce a different methodology to overcome the reverse causality bias in Chapter III. If evidence reveals that certain indicators of state fragility are related with the number of terrorist attacks, these results would provide a foundation for recognizing state at-risk characteristics and help to develop recommendations for policies and programs. Furthermore, my new findings can allow readers to determine the extent to which terrorism is endogenous to indicators of state fragility.

THIS PAGE INTENTIONALLY LEFT BLANK

III. DATA AND CODING OF THE VARIABLES

This chapter presents the data and describes the variables used in this thesis. Furthermore, it illustrates the methodology used and places it in the context of current literature. This research uses data from the GTD retrieved from the National Consortium for the Study of Terrorism and Responses to Terrorism (START) and data from the FSI provided by the Fund for Peace (FFP) (Fund for Peace, 2017; University of Maryland, 2017).

A. THE GLOBAL TERRORIST DATABASE

This thesis uses the GTD provided by START for the years 2006 to 2016. The incident-based definition of terrorism used by the GTD defines terror as “the threatened or actual use of illegal force and violence by a non-state actor to attain a political, economic, religious, or social goal through fear, coercion, or intimidation” (GTD, 2017). This definition pronounces three inclusion criteria to consider an incident to be a terroristic incident listed in the GTD. The following characteristics must be present:

The incident must be intentional—the result of a conscious calculation on the part of a perpetrator.

The incident must entail some level of violence or immediate threat of violence -including property violence, as well as violence against people.

The perpetrators of the incidents must be sub-national actors.

The database does not include acts of state terrorism

In addition, *at least two* of the following three criteria must be present for an incident to be included in the GTD:

Criterion 1: The act must be aimed at attaining a political, economic, religious, or social goal. In terms of economic goals, the exclusive pursuit of profit does not satisfy this criterion. It must involve the pursuit of more profound, systemic economic change.

Criterion 2: There must be evidence of an intention to coerce, intimidate, or convey some other message to a larger audience (or audiences) than the immediate victims. It is the act taken as a totality that is considered, irrespective if every individual involved in carrying out the act was aware of this intention. As long as any of the planners or decision-makers behind the attack intended to coerce, intimidate, or publicize, the intentionality criterion is met.

Criterion 3: The action must be outside the context of legitimate warfare activities. That is, the act must be outside the parameters permitted by international humanitarian law (particularly the prohibition against deliberately targeting civilians or non-combatants). (GTD, 2017, p. 9)

Based on these inclusion criteria, the dataset used contains information on 92,286 terrorist attacks and lists 135 different variables.

B. THE FRAGILE STATES INDEX

This thesis uses panel data from the FSI for the years 2006 to 2016. The data is compiled by the FFP and provides “an annual ranking of 178 countries based on the different pressures they face that impact their levels of fragility” (Fund for Peace, 2017, p. 3). The FSI uses a Conflict Assessment System Tool (CAST) to comprehensively triangulate “three primary streams of data—quantitative, qualitative, and expert validation—to obtain the final FSI score per country and year (Fund for Peace, 2017, p. 3). The index is designed to examine various indicators of state condition to determine a state’s relative stability and its resilience

to potential conflicts. The index is updated annually and contains data collected between January 1 and December 31 of the respective year.

The FSI covers a diverse array of 12 indicator variables categorized as cohesion, economic, political, and social indicators. The key indicators are Security Apparatus, Factionalized Elites, Group Grievances, Economic Decline, Uneven Economic Development, Human Flight and Brain Drain, State Legitimacy, Public Services, Human Rights and Rule of Law, Demographic Pressures, Refugees and Internally Displaced Persons (IDP) and External Intervention (Fund for Peace, 2017).

Each indicator variable has its own 10-point scale, which reaches from 1 to 10, where higher values indicate a higher degree of state fragility, thus designating unfavorable conditions. Accordingly, low values are an indicator of a higher level of state capacity and resilience. The aggregate score of all 12 indicator variables is given by the total FSI score and ranges from 12 to 120.

Haims, Gompert, Treverton and Stearns (2008) endorsed the FSI as an appropriate metric to determine the relative stability of a state, based on a country's total FSI score. According to this study, "countries with an aggregate score above 90 are in the 'alert' zone; countries with an aggregate score between 60 and 89.9 are in the 'warning' zone; those with an aggregate score between 30 and 59.9 are in the 'monitoring' zone; those with aggregate scores of 29.9 or below are in the 'sustainable' zone" (Haims, Gompert, Treverton, & Stearns, 2008, p. 1). Moreover, Newman examined the FSI to be the most suitable indicator of state condition in his relational assessment of FSI, the Human Development Index (HDI), and the World Bank Rule of Law, Government Effectiveness, and Political Stability indicators (Newman, 2007). Nonetheless, the design of the FSI remains proprietary to the FFP and is sometimes hard comprehend as its indicator variables are fed by further sub-indicators. An exhaustive list concerning the design of the FSI with respect to its sub-indicators can be found in Table 1 and were discussed by J. J. Messner (email to author, November 17, 2017).

C. COMPILED DATABASE

The dataset compiled for this thesis contains merged data from the GTD and the FSI. This thesis uses the incident-based definition of terrorism given by the GTD. The countries or states investigated in this analysis are all sovereign states with a membership in the United Nations (UN) and are in accordance with the list of countries used by the FSI. For the purpose of merging, I commonly used the English terminology for all countries. A derogation from the definition of a country as stated concerns the State of Israel. In my database, Israel is coded to include the West Bank and Gaza Strip. Moreover, it incorporates all observations of Palestine. Although 136 of the 193 Member States of the United Nations recognize and acknowledge the sovereignty of Palestine, I did not regard it as an entity. My coding, however, does not follow any political conviction, but pursues the most methodologically reasonable way to mitigate the impact of any associated measurement error bias.

The compiled dataset lists the number of incidents per country and year (*incperyear* variable) for the period from 2006 to 2016. In all, this set of panel data contains 1,921 observations for incidents per country and year referencing a total of 92,286 incidents. Moreover, the data contains FSI scores for 174 countries.

1. Dependent Variables

In the several models of this thesis, I use three different dependent variables. These variables are explained in the following paragraphs.

a. *Number of Incidents per Country and Year (incperyear)*

The dependent variable is *incperyear*, which is a count variable indicating the number of terrorist incidents incurred per country and year. It was derived from the GTD and coded to collapse the terror events in country year counts. This variable is the most common way scholars have operationalized terrorism in their econometric research (Young, 2016) and is therefore best suited for my analysis to obtain comparable results and evaluate them in context. Moreover, “replicating

results helps build a solid empirical foundation and points toward limits of our theories or ambiguity in the precise relationships we think occur” (Young, 2016). Furthermore, this operationalization of terrorism is appropriate to align best with the incident-based definition of terrorism introduced by the GTD.

The data of this count variable is highly overdispersed; thus, the data shows evidence that the variance of this discrete response variable Y_i is greater than $\frac{\mu_i (n_i - \mu_i)}{n_i}$.

b. Aggregated Value of Total Damage (*logtotalvalue*)

In an attempt to use a different operationalization of terrorism as recommended by Young, I conduct an analysis using the same econometric models, but with a different dependent variable (Young, 2016). In my attempt to measure the impact of terrorism, I coded my variable analogously to Rohlfs and Sullivan (2013). Although the authors presented their approach in a different context, it is a proper way to monetize the casualties associated with terror, hence, to indirectly capture the scale of terrorism.

This second dependent variable, *logtotalvalue*, expresses the logarithmic aggregate value of the total damage incurred per country and year. It is used to allow the determination of terrorism not only by the number of incidents but also in terms of magnitude. An appropriate metric to measure this scale of terrorist activities can be attained by assigning dollar values to each incident. The aggregate value of total damage is determined by the number of kills (*nkill*) and total number of wounded (*nwound*), multiplied by the value of a Statistical Life (VSL) and the Relative Disutility Factors by Injury Severity Level (MAIS) times VSL, respectively (Rohlfs & Sullivan, 2013). Both values are derived from the guidance

of the U.S. Department of Transportation, where the VSL is set to \$9.6 million¹ (U.S. Department of Transportation, 2016). The disutility factors by MAIS is set to .105 for serious and .266 for severe injuries. For my estimate, I assume an average injury level in the consequence of a terrorist attack to be between serious to severe, which yields an average disutility factor of .1855. Accordingly, the value of wounded is derived by $nwound \times (.1855 \times \$9,600,000) = \$1,780,800$. As the GTD data is not suited to derive the affected property value sufficiently, it is not included in this variable to mitigate the associated measurement error bias. Furthermore, I did not discount the amount of total damage to the net present value (NPV).

It is important to emphasize that in this context the usage of a dependent variable is not suitable to validate my initial count regression model as Young finds that the coefficient estimates of explanatory variables significantly vary across different operationalizations of terrorism. Nonetheless, accounting for the weight or intensity of terrorist acts might reveal further insights.

c. Aggregated Value of Total Kills and Total Wounded (*totalvalue*)

“Another way to operationalize terrorism ... is to count casualties or fatalities” as the magnitude of terrorism gets more obvious (Young, 2016, p. 6). Accordingly, I introduce a third dependent variable, the one of the aggregated value of total kills and total wounded (*totalvalue*). This variable is coded to sum both the numbers of persons killed (*nkill*) and numbers of persons wounded (*nwound*) collapsed to country year counts. Compared to the both previously introduced dependent variables, this regressand is a more balanced metric to operationalize terrorism. However, I did not weight *nkill* and *nwound* differently.

¹ The VSL provided by the U.S. Department of Transportation, used to derive this dependent variable, is designed for US casualties only and could differ by country. However, for the purpose of mitigating a measurement error, I attached the same dollar values to all victims, regardless their nationality, as the GTD generally allows only a distinction by US-citizen or Non-US-citizen. Moreover, this coding prevents an ethically motivated discussion about the determination of equitable value of life.

2. Independent Variables

In the following, I introduce my set of dependent variables provided by the FSI.

a. The Total FSI Score (*totalFSI*)

The total FSI Score (*totalFSI*) is an index score designed to assess a country's vulnerability to collapse. It is an indicator of a state's condition and allows us to determine the relative stability of a country. This *totalFSI* variable represents the aggregate values of in total 12 conflict risk indicator variables and provides a snapshot in time at December 31 of any year. It is rated on a 0 to 120 scale, with 0 being stable or most resilient, and 120 being most at risk (Fund for Peace, 2014).

b. Security Apparatus (*Security Apparatus*)

The indicator variable *Security Apparatus* provided by the FSI measures how peaceful security is under a government's control. Low values of this index score indicate that the government uses little to no force to maintain stability, whereas high values imply that the "monopoly on the use of violence by the state is compromised by widespread proliferation of private militias" (Fund for Peace, 2014, p. 14). This variable, furthermore, captures the impacts of terrorism a country incurs (see Appendix A), and thus measures a value that may be a result of terrorism as well as its cause. Accordingly, I handle this variable with caution to mitigate the associated endogeneity concerns.

c. Factionalized Elites (*Factionalized Elites*)

The conflict risk indicator variable *Factionalized Elites* determines the level of fragmentation of ruling elites along racial, religious, or ethnic lines. A low index score for this variable indicates the existence of a "popular and effective national leadership, with rival political interest articulated and represented through free political expression in a legitimate constitutional structure supported by the people" (Fund for Peace, 2014). Conversely, higher values designate a fractious political class unable to overcome the discords of a society with the ruling elites. It

describes the state of absence of a legitimate and broadly accepted government that fails to represent the entire citizenry, where political structures are not rooted in the majority of the society, thus lacking legitimacy and furthermore effective governance.

d. Group Grievance (*Group Grievance*)

This explanatory variable is a measure of homogeneity of a state's society. Low values imply that ethnic divisions are not delineated with sharp distinction and "individual rights and grievances are addressed through the legal and political system, civil society and free expression and advocacy" (Fund for Peace, 2014, p. 7). In contrast, high values indicate a high level of group grievance, which leads to organized acts of extreme violence such as sporadic outbursts, group-based violence, ethnic cleansing, and genocide of minorities.

e. Economy (*Economy*)

The conflict risk indicator variable *Economy* assesses the relative stability of a country's economic situation. Low values are proof of a stable and growing economy with low unemployment, a moderate inflation rate, and favorable projected indicators. Conversely, a high index score indicates a weak economy in a severe decline, experiencing a high inflation rate and a low GDP (Fund for Peace, 2014).

f. Economic Inequality (*Economic Inequality*)

This variable determines the grade of group-based real and perceived inequality. It is designed to account for the poverty level, the level of education, housing, hiring practices, and economic justice along group lines. Low values imply a low level of inequality, thus representing a high level of homogeneity, whereas higher scores describe a state of severe uneven economic development that might result in violence (Fund for Peace, 2014).

g. Human Flight and Brain Drain (*Human Flight and Brain Drain*)

The Human Flight and Brain Drain conflict risk indicator variable measures the loss of intellectuals, professionals, and political dissidents and accounts for voluntary emigration from a country. It does not describe forced migration and refugee flows. A higher index score indicates that the brain drain of a country has become chronic and sustained, which results in a significant decline of the professional and middle class of the country. Conversely, lower values are proof of a brain drain that is more balanced with brain gain; thus, it is an indication of a small risk of potential loss of the educated classes (Fund for Peace, 2014).

h. State Legitimacy (*State Legitimacy*)

This indicator variable is a measure of the amount of corruption in the government. A low score implies a low level of dishonesty within the administration and moreover functioning anti-corruption mechanisms. On the other hand, a high index score indicates an illegitimate government where corruption is endemic. The level of transparency and accountability is associated with a widespread loss of confidence in state institutions, which might result in “widely boycotted or flawed elections, mass public demonstrations, civil disobedience, and inability of the state to collect taxes, resistance to military conscription,” and “rise of armed insurgencies” (Fund for Peace, 2014, p. 11).

i. Public Services (*Public Services*)

The Public Services conflict risk indicator variable “refers to the lack of, or disappearance of, basic state functions that serve the people” (Fund for Peace, 2014, p. 12). A low score indicates that public services are well developed and accessible in both urban and rural areas. Conversely, high values are proof of a deteriorated public service infrastructure.

j. Human Rights (*Human Rights*)

The indicator variable for Human Rights is a measure of “abuse of legal, political and social rights, including those of individuals, groups and institutions

(e.g., harassment of the press, politicization of the judiciary, internal use of military for political ends, public repression of political opponents)” (Fund for Peace, 2014, p. 12). States that apply human rights “equally to all on all levels” are considered to be stable with respect to this indicator, and thus have a low index score. In contrast, those states that systematically harass minorities and violate human rights are designated with a high score value (Fund for Peace, 2014, p. 12). Simultaneously, civil society and open media declines with an increase of this index value.

k. Demographic Pressures (*Demographic Pressures*)

The Demographic Pressures conflict risk indicator variable reflects the grade of demographic pressure arising from population density, group settlement patterns, population growth rates, and a skewed population distribution. Furthermore, it accounts for pressure stemming from natural disasters, epidemics, and environmental hazards. High score values are evidence of a high level of demographic pressure affecting large segments of the population and “massive threats to livelihood” (Fund for Peace, 2014, p. 5). Meager demographic pressure is associated with a low index score.

l. Refugees and Internally-Displaced Persons (*Refugees and IDPs*)

A state’s vulnerability caused by refugees and migrations is assessed by the Refugees and IDPs variable. It measures the numbers of refugees and internally-displaced peoples fleeing or entering a region/country as well as the level of absorption in the host society. The bigger the influx of refugees and the lower the level of absorption in the host country, the more vulnerable a country is to these migration movements. Thus, this results in a higher score value (Fund for Peace, 2014).

m. External Intervention (External Intervention)

The External Intervention indicator variable measures the extent of the full spectrum of means of external interventions. Relatively moderate types of intervention, indicated by lower scores, are economic interventions by external actors, including non-governmental organizations (NGOs), development projects, and foreign assistance. More powerful means of external interventions are military engagements such as covert and overt interventions, externally supported militia, and in its strongest form, peacekeeping missions (Fund for Peace, 2014).

3. Evaluation of the Data

The data used in my thesis are open source data and not purposefully collected to be a perfect fit to find answers to my research questions. Accordingly, it is important to acknowledge that some bias might arise from my database. The fact that the data were collected along conventional political borders rather than clans, ethnicities, and religious denominations might dilute my results in terms of significance. However, this measurement problem is mitigated as my data are coded to match GTD and FSI along the same geographic entities. Another problem arises from the data coming from the GTD. The data provided by this database, and subsequently used in this thesis, include information about worldwide terrorist attacks that reportedly occurred between 2006 and 2016. This incident-based database implies an underreporting bias as the data are based on open media sources (GTD, 2017). “The essence of underreporting is the suspicion that observed terrorist events might well not correspond to the actual numbers of attacks, as only the events that found their way into open sources, such as the media, have actually been reported” (Drakos & Gofas, 2016, p. 715). Especially data from states known to censor or control media might be biased. The observation of considerable zeros for nondemocratic countries (e.g., North Korea) on the one hand, and the increasing number of reported terrorist attacks for states with higher levels of polity, on the other hand, are indicators of an attributable issue with the data, resulting in an underreporting bias for countries with suppressed

media and an “encouragement-effect” for countries with open media (Drakos & Gofas, 2016, p. 715). This “encouragement-effect” suggests the number of terrorist events increases along with the level of democratization (Drakos & Gofas, 2016, p. 715) and implies an endogeneity issue creating a reverse causality bias that must be accounted for and is eliminated with Model 5 and Model 7.1 of my analysis. The gap resulting from the underreporting bias, representing the difference between reported and actual events, is of lesser significance, in the case that this error was uncorrelated with the country characteristics. However, Drakos and Gofas found evidence that this problem relates to press freedom (Drakos & Gofas, 2016). Hence, this bias has implications for a country level analysis of terrorism and requires a thoughtful explanation in terms of magnitude. Nonetheless, the GTD provides the most comprehensive data on terrorist events worldwide and has become a well-recognized standard for data-driven research on the phenomenon on terror (Kis-Katos et al., 2012). Given the limitations induced by the underreporting bias, this database provides the most accurate information available. It, furthermore, “can be used in conjunction with other data (e.g., political or economic indicators) in analyses of the causes and consequences of terrorism and can contribute information to analyses of how, when and why and [sic] terrorism events and campaigns decline or end” (Sheehan, 2011, p. 24).

With respect to the data provided by the FSI, it is important to admit other possible sources of biases. This index is designed to examine various indicators of state condition to determine a state’s relative stability and its resilience to potential conflicts. The proprietary CAST framework used to measure this level of stability takes advantage of huge quantities of data and incorporates several hundred sub-indicators that flow into the 12 conflict risk indicator variables (Fund for Peace, 2017). As a result of this comprehensive approach, the indicator variable *Security Apparatus* is designed to partially account for the level of terrorism occurring in a country. Against the background of my analysis, this implies a bias if I included this variable in my models, as it accounts for terrorism in the dependent and the explanatory variable at the same time. Consequently, I

do not include this variable to alleviate this bias; however, at the same time, I might lose valuable data by my attempt to prevent collinearity. Furthermore, the span and the bandwidth of the conflict risk indicator variables are large, whereas the scale of each variable is relatively small as it is limited to values from 1 to 10. For example, the number of fleeing refugees, expressed by the variable's *Refugees and IDPs* index score, varies from several hundred (score of 7) to millions (score of 10) within a range of just four index points. Another example describing this enormous span is given by the *External Intervention* variable, which accounts for all types of instruments of external interventions, namely relatively moderate types of intervention, such as economic interventions and development projects, but also more powerful means like military engagements and peacekeeping missions. Knowing about these circumstances and given a reasonable confidence level (95%), it requires thoughtful explanations and circumspection to explain the results of my analysis of the fragility-terrorism nexus.

THIS PAGE INTENTIONALLY LEFT BLANK

IV. METHODOLOGY

The purpose of this research with a non-experimental descriptive design is to examine and discern the underlying relationship of state fragility and the phenomenon of terrorism. Furthermore, it can help to identify certain characteristics of state fragility that are associated with the occurrence of terrorist activities. The primary research question of this thesis is:

- What characteristics make states susceptible for terrorist attacks?

If evidence of the findings reveals that certain indicators of state fragility are strongly correlated with the likelihood of terrorist attacks, it would be interesting to quantify the magnitude of the associated risk. Once determined, these results would provide a foundation for recognizing state at-risk characteristics and help to develop recommendations for policies and programs to address those factors. The secondary research question of this thesis addresses this problem as follows:

- How do indicators of state fragility affect the likelihood of terrorist attacks and to what extent?

The approach of my research is threefold. In a first step, I adapt the most common regression model used in this field of research to investigate the relationship of the numbers of terrorist attacks and state fragility (Kis-Katos et al., 2012; Gassebner & Luechinger, 2011). As the data is highly overdispersed, the appropriate count regression model is the negative binomial regression model (NBR). It is “best suited to accommodate these data [...] and has become the standard model in the empirical analysis of terrorism” (Kis-Katos et al., 2012, p. 13). In accordance with several scholars, this thesis includes fixed effects to properly account for country specific characteristics (Kis-Katos et al., 2012; Gassebner & Luechinger, 2011).

All estimated coefficients in this thesis are reported in incidence-rate ratios (IRR), that is e^{β_i} rather than β_i , to allow an interpretation not only in terms of

significance and direction but also in terms of magnitude. Accordingly, IRR can be interpreted similarly to the odds ratio in a logistics regression model. To be able to evaluate the performance of the developed models with respect to how well they approximate and explain the data, the Akaike information criterion (AIC) and Bayesian information criterion (BIC) are reported for each model. Both information criteria allow the selection of econometric models across a pool of candidate models and concurrently prevent an overfitting of the model, as they penalize excessive use of variables, artificially inflating the models. Lower values for AIC and BIC designate the best model out of the pool of candidate models.

Using the industrial standard of regression analysis for my first model should not obscure the fact that the NBR does not appropriately account for the role of endogeneity in this fragility-terrorism nexus that stems from a reverse causality bias, as fragility might lead terrorism, which consequently destabilizes a country. Given this fact, it is reasonable to assume that terrorism has a self-sustaining potential. In general, only a few scholars have addressed these implications of a reverse causality bias in their attempts to identify determinants of terrorism (Kang & Lee, 2005; Krieger & Meierrieks, 2011; Meierrieks & Gries, 2013). To overcome the fact that endogeneity plagues this most common econometric model to estimate the fragility-terrorism nexus, I conduct an instrumental variable (IV) approach in a second step (Model 5). An Arellano-Bond Dynamic Panel Generalized Method of Moments (GMM) Estimator (Arellano-Bond Estimator) and the available longitudinal data provide plausible instruments to overcome this reverse causality bias (Arellano & Bond, 1991). This linear Dynamic Panel Regression Model uses two lags of the dependent variable included as additional regressors and furthermore treats all explanatory indicator variables as endogenous variables. The model uses a robust variance estimator to obtain robustness against heteroskedasticity. On the assumption the instrumental variables are valid and that there is no autocorrelation in the idiosyncratic errors, this model allows for the identification of true causal effects rather than simple correlations.

The third step is a comparison of the outcomes of the NBR models with the causal implications derived from the linear Dynamic Panel Regression Model from step two, which evaluates the impact of the endogeneity problem in the fragility-terrorism relationship. Ultimately, I draw conclusions about the applicability of the NBR as the most common regression model used in the field of research for finding determinants of terror.

A. INTRODUCTION OF THE DIFFERENT MODELS

In the course of this thesis I introduce in total seven different models. The first four models are estimated by the NBR technique, and thus are designed to comply with the ‘industrial standard’ in the empirical research area about terrorism (Kis-Katos et al., 2012). In the remaining three models and their enhancements, I use the Dynamic Panel GMM approach introduced by Arellano and Bond (Arellano & Bond, 1991) to address an endogeneity issue in the fragility-terrorism nexus. In an attempt to validate my findings, I use three different operationalizations of terrorism introduced in Chapter III with Model 7.1, Model 7.2, and Model 7.3.

1. The Negative Binomial Regression Models

In the following segment I will introduce my models using the NBR technique.

a. Model 1: Number of Terrorist Attacks and State Fragility

The dependent variable in Model 1 to Model 7.1 is the number of incidents per country and year (*incperyear*). The set of panel data used contains state-level data that observe the same units (FSI scores) at different points in time. My Y and X variables are dated contemporaneously. The model relating Y to X in this time-series analysis is shown in Equation (1):

$$Y_{it} = \alpha + \mathbf{X}'_{it}\boldsymbol{\theta} + v_{it} \quad (1)$$

where my dependent variable, the number of terrorist attacks, is denoted by Y_{it} in country i and year t . The vector \mathbf{X}' is the set of my control variables given by the FSI and v_{it} is the error term.

The first model of this thesis (Model 1) is designed to examine the relationship between the number of terrorist incidents and the respective stability of a country in a year using the NBR model including fixed effects. It is not designed to explicitly find causation. Its purpose is to replicate the results from Piazza by taking advantage of panel data and to consider whether the security concerns associated with weak or failing states are observable and verifiable in the data and therefore justify a further and more detailed investigation (Piazza, 2008; POTUS, 2017). Accordingly, the dependent variable in Model 1 is *incperyear* and the explanatory variable is the aggregate FSI score per country and year (*totalFSI*). The results of Model 1 are shown in Table 1 in Chapter V. All coefficient estimates are reported in incident rate ratios.

b. Model 2: Raw Data Analysis—Number of Terrorist Attacks and State Fragility

As mentioned before, the FSI is designed to examine various indicators of state condition to determine a state's relative stability and its resilience to potential conflicts. This index covers a broad array of in total 12 cohesion, economic, political, and social indicators. Model 2 takes advantage of these more detailed data to conduct a raw data analysis. Again, a negative binomial regression analysis using fixed effects is the model of choice. Whereas Model 1 estimates a joint effect of all 12 indicator variables at a time, and therefore provides a coefficient estimate that must be interpreted as a weighted average of these, Model 2 assesses the associated numbers of terrorist attacks of every single indicator. This allows a more precise estimation of the single attribute's impact on the number of terrorist incidents.

In Model 2, *incperyear* remains the dependent variable, and only one of my indicator variables at a time, one after the other, is regressed on it. The resulting coefficient estimates report the numbers of terrorist attacks associated with every single indicator variable in IRR. Appendix B shows the results from this raw data analysis.

c. Model 3: Long Model—Joint Estimate of the Indicator Variables' Impact

Model 3 is designed to estimate the joint impact of the indicator variables on the number of terrorist attacks. However, it includes just 11 out of the 12 indicator variables at a time. The indicator variable *Security Apparatus* was omitted for collinearity reasons as this variable already incorporates terrorist attacks as one of its sub-indicators and furthermore to mitigate any resulting measurement errors. The results of this estimation are shown in Table 2 in Chapter V. Again, all coefficient estimates are reported in IRR.

d. Model 4: Best Fitted Model—Number of Terrorist Attacks and Indicators of State Fragility

Model 4 is the best fitted model given the data and based on the knowledge gained from my previous models. Again, it accounts for the aforementioned reverse causality problem as it does not include the indicator variable *Security Apparatus*.

It relates the previously found statistically significant explanatory indicator variables *Economic Inequality*, *Public Services*, *Demographic Pressures*, *Refugees and IDPs*, and *State Legitimacy* to the number of terrorist attacks and further controls for *Group Grievance*, *Economy*, *Human Flight and Brain Drain*, and *Factionalized Elites*. Like all previous models, this model includes fixed effects, and the coefficient estimates are reported in incident rate ratios. The results of this regression model are shown in Table 3 in Chapter V.

2. Finding Causality with the Arellano-Bond Estimator

As argued earlier, endogeneity plagues the most common econometric model to estimate the fragility-terrorism nexus. To overcome this reverse causality bias I take advantage of my panel data, which can provide insight into the underlying dynamics of the relationship that is subject to investigation in this thesis. Consequently, I conduct an IV approach in the next step (Model 5 to Model 7.3)

by using the Arellano-Bond Estimator, which was designed for panels with small periods and large Ns (Arellano & Bond, 1991).

Accordingly, the equation introduced in Model 1, which estimates the impact of state fragility on the number of terrorist attacks in a panel dataset, as further modified in this model, is denoted by:

$$Y_{it} = \alpha + \beta_1 Y_{i,t-1} + \mathbf{X}'_{it} \boldsymbol{\theta} + \mathbf{Z}'_{i,t-1} + v_{it} \quad (1)$$

where Y_{it} represents the number of terrorist attacks and $Y_{i,t-1}$ is its lagged value. Furthermore, \mathbf{X}' is my matrix of the included fragility indicator variables and \mathbf{Z}' represents the matrix of the corresponding lagged values of my endogenous regressors used as further instruments. By first differencing all regressors, the Arellano-Bond Estimator transforms Equation (1) into:

$$\Delta Y_{it} = \alpha + \beta_1 \Delta Y_{i,t-1} + \Delta \mathbf{X}'_{it} \boldsymbol{\theta} + \Delta \mathbf{Z}'_{i,t-1} + \Delta v_{it} \quad (2)$$

making the endogenous variables pre-determined as they get instrumented with their past levels and, thus, are no longer correlated with my error term in Equation (1). In case the lagged variable is still correlated with the error term, a higher order lag is used as an instrument instead. Under the assumption that the Xs were initially correlated with the error term, the first differencing now provides valid instruments for all pre-determined or strictly endogenous variables (Arellano & Bond, 1991). The resulting coefficient estimates become unbiased as they are no longer correlated with the initial error term.

a. Model 5: Short Model Using Arellano-Bond Estimator

As I did for Model 1, I investigate the relationship between state fragility and the number of terrorist attacks with Model 5. In particular, I use a two-step Arellano-Bond Estimator for this model, which uses one lag of the dependent variable included as additional regressors and furthermore treats all explanatory indicator variables as strictly endogenous variables. Additionally, my Model 5 uses a robust variance estimator to obtain robustness against heteroskedasticity. I tested several lag structures and found that a two-step model with varying numbers of lags was needed to pass the specification tests that are compulsory for this methodology.

My model satisfies the condition of the test for autocorrelation provided by Arellano and Bond and was obtained with the Stata command 'estat abond' (Arellano & Bond, 1991). This post-estimation provides evidence that the first Arellano–Bond Estimator model assumption is satisfied as there is a first-order serial correlation of the differenced errors but not a second-order correlation. In the second specification test, I examined the validity of my instruments with the Sargan Test by using the Stata command 'estat sargan.' This test for overidentifying restrictions provides evidence that the generated IV are healthy and acceptable instruments. Thus, it is legitimate to conclude that Model 5, using the Arellano Bond Estimator, allows the identification of true causal effects rather than simple correlations found in Model 1 to Model 4.

The coefficient estimates reported using the Arellano-Bond Estimator are shown in Table 4 in Chapter V.

b. Model 6: Raw Data Analysis Using Arellano-Bond Estimator

As I did to my Model 2 using the NBR, I conduct a raw data analysis in this chapter to find the true causal effects of each single indicator of state condition on the number of terrorist attacks. Accordingly, my linear Dynamic Panel Regression Model uses each of the 12 cohesion, economic, political, and social indicators sequentially. I tested several lag structures to specify a two-step Arellano-Bond Estimator with varying numbers of lags to satisfy the requirements of the post-estimation tests. I include lags of the dependent variable as additional regressors and moreover treat the indicator variable to be endogenous to the number of terrorist attacks. As in the previous model, I use a robust variance estimator to obtain robustness against heteroskedasticity. Appendix C shows the results from this raw data analysis.

c. Model 7.1: Best Fitted Model—Number of Terrorist Attacks and State Fragility (Arellano-Bond Estimator)

A more sophisticated version of Model 5 and Model 6, using several indicator variables of the FSI, allows for a more detailed insight as it further

disentangles the nexus of fragility and terrorist activities. As I did previously, I use a two-step Arellano-Bond Estimator with the robust variance estimator to obtain robustness against heteroskedasticity. Model 7.1 includes three lags of the dependent variable as additional regressors and furthermore treats all explanatory indicator variables as strictly endogenous variables. The diagnostics of the two required post-estimations techniques prove Model 7.1 to be valid.

The coefficient estimates reported in Table 5 of Chapter V show the causal impacts of the respective indicators of state fragility on the number of terrorist attacks.

d. *Model 7.2: Best Fitted Model—Logged Total Value (in \$) and State Fragility (Arellano-Bond Estimator)*

Following the recommendation of Young to use a different operationalization of terrorism, I utilize the alternative dependent variable *logtotalvalue*, introduced in Chapter III (Young, 2016). In Model 7.2, this variable expresses the logarithmic aggregate value of the total damage incurred per country and year. It is designed to allow the determination of terrorism not only by the number of incidents but also in terms of magnitude.

Model 7.2 is similar to Model 7.1 and uses a robust two-step Arellano-Bond Estimator to obtain robustness against heteroskedasticity. Instead of the previously used three lags, it includes one lag of the dependent variable as an additional regressor and furthermore treats all explanatory indicator variables as strictly endogenous.

The coefficient estimates reported in Table 6 in Chapter V show the causal impacts of the indicators of state fragility on the aggregate value of the total damage.

e. *Model 7.3: Best Fitted Model—Total Number of Fatalities and State Fragility (Arellano-Bond Estimator)*

In Model 7.3, I treat the aggregate value of total kills and total wounded (*killnwound*) as my dependent variable. Compared to both previously introduced

regressands, this dependent variable is a more balanced metric to operationalize terrorism. Model 7.3 uses a robust two-step Arellano-Bond Estimator and includes three lags of the dependent variable as additional regressors. The explanatory indicator variables are treated to be strictly endogenous. My post-estimation results prove Model 7.3 to be valid. The coefficient estimates reported in Table 7 of Chapter V show the causal impacts of indicators of state fragility on the aggregate value of total kills and total wounded.

THIS PAGE INTENTIONALLY LEFT BLANK

V. RESULTS

A. RESULTS FROM THE NEGATIVE BINOMIAL REGRESSION MODELS

This chapter's purpose is to present and to discuss the results from this research's models introduced previously. First, I present the results from the NBR models. In a second step, later in this chapter, I present the outcomes from this research's models using the Arellano-Bond Estimator.

1. Model 1: Number of Terrorist Attacks and State Fragility

The results of the estimation from Model 1 are shown in Table 1. All coefficient estimates are reported in incident rate ratios.

Table 1. Model 1

Model 1: Number of Terrorist Attacks and State Fragility	
incperyear	.
	[.]
total FSI score	0.993***
	[0.002]
Observations	1,871
Number of countries	173
N	1871
*** p<0.01, ** p<0.05, * p<0.1	
Coefficient estimates reported in Incident Rate Ratios (IRR)	

The coefficient estimates provide strong and statistically significant evidence that demonstrate fragility is associated with the number of terrorist incidents. The finding is of little economic significance as the reported coefficient estimate for *totalFSI* is close to 1 and the associated number of terrorist attacks decreases by .7% with every one-unit increase of the total FSI score. Nevertheless, the latter conclusion is surprising, as it implies that more fragile countries, on average, experience fewer terrorist attacks than more stable countries, a finding which is contrary to Piazza (2008), who found statistical

evidence that "states experiencing intense state failures are statistically more likely to be the target of attacks and are more likely to have their nationals commit attacks overseas" (p. 481).

A reason for this rather unexpected result might be attributed to the underreporting bias for states known to censor or control media described in Chapter III.

The AIC and BIC for Model 1 are 8,435.97 and 8,447.04, respectively.

2. Model 2: Raw Data Analysis—Number of Terrorist Attacks and State Fragility

The coefficient estimates of Model 2 shown in Appendix B reveal that eight out of the 12 indicator variables have a statistically significant relationship with the number of terrorist attacks. These moreover economically significant variables are Factionalized Elites^{***}, Group Grievance^{***}, Economic Inequality^{***}, Human Flight and Brain Drain^{***}, State Legitimacy^{***}, Human Rights^{***}, Demographic Pressures^{***}, and Refugees and IDPs^{*}.

The coefficient estimates of each single indicator variable are smaller than 1; thus, they indicate a negative relationship with the number of terrorist attacks. These results are interesting as they back my findings from Model 1 that more fragile countries, on average, experience fewer terrorist attacks than more stable countries. The variables with the biggest magnitude are Economic Inequality^{***} with on average 16.83% fewer incidents per one-unit increase of the FSI score and Human Rights^{***} with 9.09%, respectively.

Again, these findings do not match Piazza's results but support my outcomes from Model 1 that fragile states experience less terrorist activities. Yet, this does not tell much about these countries' resilience against terrorism, as it might just be that fragile states are simply not a worthwhile target for terrorists. On the other hand, this result can be interpreted analogously to Mansfield and Snyder's concept of an inverted U (Mansfield & Snyder, 1995). The authors found evidence that the war-proneness of a country depends on the degree of its level

of democratization and that strong autocracies tend to have the least risk to be involved in a war compared to those states in transition. This argument finds further support by Findley and Young who found evidence that regimes in transition are more likely to be faced with terrorism (Findley & Young, 2011) and moreover by Blomberg et al., who showed that countries at intermediate levels of social diversity provide an environment that induces terrorist activities (Blomberg et al., 2011). A very similar result was published by Krieger and Meierrieks (2011), who found evidence terrorism can emerge as a result of a political transformation process, which enhances political vacuums. In this context, it seems reasonable to assume that the incidence of terror does not follow a strictly linear pattern, other than that found by Piazza (2008).

Nevertheless, the insights from my raw data analysis should not be overrated, as a country's stability can never be determined by a single indicator variable. The complexity of the concept of state fragility clearly demands the inclusion of more than just one explanatory variable.

3. Model 3: Number of Terrorist Attacks and Indicators of State Fragility

The results of my estimation from Model 1 are shown in Table 2. All coefficient estimates are reported in incident rate ratios.

Table 2. Model 3

Model 3: Number of Terrorist Attacks and Indicators of State Fragility	
incperyear	. [.]
Factionalized Elites	1 [0.037]
Group Grievance	0.986 [0.033]
Economy	0.979 [0.029]
Economic Inequality	0.766*** [0.029]
Human Flight and Brain Drain	1.031 [0.031]
State Legitimacy	0.947 [0.041]
Public Services	1.266*** [0.049]
Human Rights	0.982 [0.037]
Demographic Pressures	0.881*** [0.037]
Refugees and IDPs	1.049** [0.024]
External Intervention	1.023 [0.031]
Observations	1,871
Number of countries	173
N	1871

*** p<0.01, ** p<0.05, * p<0.1

Coefficient estimates reported in Incident Rate Ratios (IRR)

The statistically significant variables of Model 3 are Economic Inequality, Public Services, Demographic Pressures, and Refugees and IDPs, all of which are economically significant, too. The coefficient estimates reported in Table 4 indicate that a one-unit increase of the index score for Economic Inequality is associated with a decrease in the number of terrorist attacks by 23.4%. Furthermore, Demographic Pressures is also associated with a negative impact on the number of incidents, with an 11.8% decrease of terrorist attacks per one-unit increase of the index score.

Instead, Public Services and Refugees and IDPs are positively related with the number of terrorist attacks. A one-unit increase of the score is associated with an increase in the numbers of incidents by 26.6 % or 4.9%, respectively. The AIC and BIC for Model 3 are 8328.969 and 8395.38, respectively; thus, this model approximates and explains the data better than Model 1 does.

4. **Model 4: Best Fitted Model—Number of Terrorist Attacks and Indicators of State Fragility**

In comparison with my other NBR models, Model 4 seems to be fitted best, as the post-estimation for AIC and BIC reports the lowest values with 8325.865 and 8381.207, respectively. The results of my estimation from Model 4 are shown in Table 3. Again, all coefficient estimates are reported in incident rate ratios.

Table 3. Model 4

Model 4 - Best Fitted Model: Number of Terrorist Attacks and Indicators of State Fragility	
incperyear	. [.]
Economic Inequality	0.762*** [0.029]
Public Services	1.268*** [0.049]
Demographic Pressures	0.881*** [0.036]
Refugees and IDPs	1.052** [0.024]
State Legitimacy	0.939* [0.034]
Group Grievance	0.986 [0.032]
Economy	0.985 [0.029]
Human Flight and Brain Drain	1.036 [0.031]
Factionalized Elites	1.002 [0.037]
Observations	1,871
Number of countries	173
N	1871

*** p<0.01, ** p<0.05, * p<0.1

Coefficient estimates reported in Incident Rate Ratios (IRR)

All the explanatory variables of Model 4 are statistically significant at the 2% level or even better, except for the variable *State Legitimacy*, which is significant at the 8.7% level. Moreover, all of my findings are economically significant, too. The coefficient estimates of the indicator variables *Public Services* and *Refugees and IDPs* express a positive relationship with my dependent variable, whereas the remaining three explanatory variables are associated with decreasing numbers of terrorist attacks.

My results indicate that a one-unit increase in the score of the indicator variable *Public Services* is associated with a 26.8% increase of incidents. Furthermore, they provide evidence that as a country's refugee situation worsens by one unit, it is related to a 5.2% higher number of terrorist incidents.

In contrast, a worsening uneven economic development (*Economic Inequality*) by one unit is correlated with a 23.8% decrease in incidents. The same negative relationship is reported for *Demographic Pressures* with an associated decrease by 11.89% per one-unit increase of the index score and *State Legitimacy* with a 6% decrease, respectively.

5. Discussion of the Results of the NBR Models

The coefficient estimates of Model 1 provide highly significant statistical evidence that state fragility is associated with the number of terrorist incidents. Model 1 offers a strong indication that there is a consistent relationship between the number of terrorist attacks and the level of state fragility. However, Model 1 is not suitable to derive a conclusion in terms of magnitude as the level of economic significance is very close to zero (-0.7%). This very weak economically negative association between my variables asks for further investigation to disentangle the associated effects of the several indicator variables that are provided by the FSI and to identify the at-risk characteristics of a country. Accordingly, I included these 12 indicator variables in my next model to investigate how they are intertwined with each other. In a first step, the results of my raw data analysis (Model 2) consolidate the outcomes from Model 1, which indicates a weak negative relationship between

X and Y in terms of magnitude. I found that all single indicators variables, independently regressed on my dependent variable, are negatively correlated with the number of terrorist attacks, regardless of their statistical significance. This is a very interesting result, as it would debunk Piazza's finding (2008) that fragile states are significantly more susceptible to terrorist attacks.

The joint estimation of the several indicator variables provided by the FSI conducted with Model 3 allows a more detailed analysis of the nexus of terrorism and state fragility. This more sophisticated version of Model 1 is designed to take advantage of the broad data and furthermore acknowledges and addresses an issue of collinearity associated with the indicator variable Security Apparatus. Model 3 reveals evidence that some indicator variables are positively associated with my dependent variable, thus indicating that a worsening of Public Services and a country's refugee situation are correlated with an increase in terrorist attacks.

It is important to admit that all my NBR models are not designed to find causal impacts; thus, they estimate correlations between state fragility and the number of terrorist attacks. More importantly, it is necessary to acknowledge this methodology does not appropriately account for the role of endogeneity in this fragility-terrorism nexus, which stems from a reverse causality bias, as fragility might lead terrorism and consequently destabilizes a country.

To conclude about potential significant causal effects between indicators of state fragility and the incidence of terrorism, I have to refer to the results from my Models 5 to Model 7.3.

B. RESULTS FROM THE ARELLANO BOND ESTIMATOR MODELS

In this section I present and discuss the outcomes of my models using the Arellano-Bond Estimator.

1. Model 5: Number of Terrorist Attacks and State Fragility (Arellano-Bond Estimator)

The results of my estimation from Model 5 are shown in Table 4.

Table 4. Model 5

Model 5: Number of Terrorist Attacks and State Fragility (Arellano-Bond Estimator)	
incperyear	
L1.	0.791*** [0.111]
total FSI score	-6.093 [3.771]
Observations	1,531
Number of countries	173
N	1531

*** p<0.01, ** p<0.05, * p<0.1

Model 5 provides statistical evidence of borderline significance ($p=.106$) that a higher total FSI score, in other words more fragile countries, on average incur fewer terrorist attacks compared to more stable states. This finding is in accordance with my results from Model 1, but to a different extent. Yet it contradicts Piazza who found that relationship to be positive (Piazza, 2008). Moreover, Model 5 allows the determination of the instantaneous effect of the total number of terrorist attacks in this period on the total number of incidents in future. Consequently, the first lag of the dependent variable can explain an increase in terrorist attacks in the period thereafter. There is no statistical evidence, however, that it will also impact terrorism in the period after next.

My findings reveal that a terrorist attack in this period entails .79 terrorist attacks in the next period. In the course of this, the reverse direction of this lagged independent variable's impact on the number of terrorist attacks relative to the effect of the *totalFSI* variable dilutes the total effect and requires attention with respect to the accurate interpretation of this model's outcomes. This is especially true as the magnitude of this reciprocal effect is quite remarkable. Regardless the ultimate quantitative extent of this causal relationship, my results provide two

important insights. First, fragile countries on average incur fewer terrorist attacks than the more stable countries, and second, the anticipated reverse causality bias in the fragility-terrorism nexus proves to be a matter of fact at the highest level of significance. Consequently, it is legitimate to conclude that terrorism has a self-sustaining potential in the short term, as terrorist attacks do have an instantaneous effect on terrorist activities in the next period.

The results of the following models allow a more detailed insight into the fragility-terrorism relationship and attest to this borderline significant outcome being reasonably valid.

2. Model 6: Raw Data Analysis—Number of Terrorist Attacks and State Fragility (Arellano-Bond Estimator)

The results of my estimation of Model 6 are reported in Appendix C. The coefficient estimates reveal that four out of the 12 indicator variables have a statistically significant relation with the number of terrorist attacks. These also economically significant variables are *Group Grievance* ($p=.049$), *Economic Inequality* ($p=.097$), *Human Flight and Brain Drain* ($p=.049$), and *External Intervention* (.042). The indicator variable *State Legitimacy* is of borderline significance at a p-value of .108. Moreover, the first additional regressors of the lagged dependent variable prove all to be a statistically highly significant ($p=.00$) cause for the numbers of terrorist attacks in the next period, but not for the period thereafter. This relationship is robust as it supports my results from Model 5 as the single indicator variable's coefficient estimates are distributed over a relatively small effect-size interval ranging from .7591 to .8065.

The coefficient estimate of the *Factionalized Elites** variable is positive, thus indicates that more fragile states are likely to incur more terrorist attacks. Conversely, all remaining significant coefficient estimates do have a lessening effect on terrorists' activities. Again, these findings don't match Piazza's results but support my findings from Model 1 and Model 5 (Piazza, 2008).

Beside these statistically significant findings, it is also important to pay attention to those indicator variables which are incapable to explain terrorism in this raw data analysis, thus, are at best suitable to be included as control variables in my next models. The variables *Factionalized Elites*, *Public Services*, *Human Rights*, *Demographic Pressures*, and *Refugees and IDPs* and *Economy* to the highest extend, are all shown to be statistically insignificant, though again reveal a predominantly downward direction. With respect to literature or rather the public perception, the association of migration-induced influx of refugees and terrorism is extremely controversially discussed (Randahl, 2016; Choi & Salehyan, 2013).

Allover, these sometimes-contrasting single indicator variable's impacts on my dependent variable make it worthwhile to investigate the causal relationships in a more comprehensive model. I will present the findings in the following chapter.

3. Model 7.1: Best Fitted Model—Number of Terrorist Attacks and State Fragility (Arellano-Bond Estimator)

Model 7.1 is a comprehensive model designed to discern a causal relationship in the terrorism-fragility nexus and to address the issue of endogeneity in this association. The results of my estimation are reported in Table 5.

Table 5. Model 7.1

Model 7.1: Best Fitted Model - Number of Terrorist Attacks and State Fragility (Arellano-Bond Estimator)	
Incpyear	
L1.	0.678*** [0.057]
L2.	-0.178 [0.195]
L3.	0.308 [0.335]
Factionalized Elites	106.499* [59.046]
Economic Inequality	64.295* [34.034]
Human Flight and Brain Drain	-95.443* [49.102]
Public Services	-16.997 [35.699]
External Intervention	-97.694* [50.851]
State Legitimacy	11.641 [28.883]
Observations	1,185
Number of countries	173
N	1185

*** p<0.01, ** p<0.05, * p<0.1

Once endogeneity is properly accounted for by means of my IV approach, a worsening of some of a country's stability factors can solidly predict an increase in terrorist attacks. Consequently, the identified and statistically significant positively related root causes for terrorism are *Factionalized Elites* (p=.071) and *Economic Inequality* (p= .059).

This finding of inequality causing terrorism is consistent with the theory of relative deprivation, which contends that frustration over the distribution of resources will increase the potential for conflicts and collective violence (Gurr, 1970). Relatively low opportunity costs for violence and an inciting frustration can be an explanation for this relation. Krieger et al. have argued that "terrorist organizations should find it easier (less costly) to recruit frustrated followers or to receive funding from supporters when economic deprivation prevails" (Krieger et al., 2011, p. 6). They add that "the lack of non-violent economic activities may also fill the ranks of terrorist organizations by lowering the opportunity costs of violence"

(Krieger & Meierrieks, 2011, p. 6). In a different paper Krieger and Meierrieks found robust causal evidence that “higher levels of income inequality result in more terrorist activity” by using an IV approach (Krieger & Meierrieks, 2011, p. 1).

With respect to *Factionalized Elites*, which was insignificant in the previous model, the level of fragmentation of ruling elites along racial, religious, or ethnic lines determines the number of terrorist attacks. In this model, the indicator variable *Factionalized Elites* becomes an important determinant of terrorism and my findings are further backed by the literature (Kis-Katos et al., 2012; Schulz, 2015). The coefficient estimate of this explanatory variable is the most significant of all my estimates, both in statistical and economic terms and shows that the more divided a national leadership is, the more often a country suffers from terrorism. In detail, a one-unit increase of the index score causes 104 additional terrorist attacks on average, holding all other variables constant. Apparently, a fractious political class is highly susceptible to terrorist attacks as it is less able to overcome the discords of a society with the ruling elites. An explanation for this causal relationship can be the absence of a legitimate and broadly accepted government that fails to represent the entire citizenry. Political structures that are not rooted in the majority of the society, thus lacking legitimacy and furthermore effective governance, seem to induce terrorist attacks. In this context, though, it is presumably inefficient governance rather than the lack of legitimacy that is the main reason, as the control variable *State Legitimacy* remains highly insignificant ($p=.69$) in Model 7.1. This violence inducing mechanism can be explained with the coercion theory, which assumes that “it is not voluntary cooperation or general consensus but enforced constraint that make social organizations cohere. In institutional terms, this means that in every social organization some positions are entrusted with a right to exercise control over other positions in order to ensure effective coercion; it means, in other words, that there is a differential distribution of power and authority.... This differential distribution of authority invariably becomes the determining factor of systematic social conflicts of a type that is germane to class conflicts in the traditional sense of the term” (Dahrendorf, 1959,

p. 165). Consequently, a lack of coercive power ultimately leads to a higher level of violence or in this specific context, analogously to an increase of terrorist attacks.

As already found in the previous model, Model 7.1 proves that the total number of terrorist attacks in this period has implications for the total number of incidents in future, as the first lag of the dependent variable can significantly explain an increase in terrorist attacks in the period thereafter. Again, I find that the effect is only of relatively short duration. There is no statistical evidence that the total number of terrorist attacks in period one (t) will also impact terrorism in the period after next or in the period thereafter ($t+2$ and $t+3$). My findings reveal that a terrorist attack in this period entails .68 terrorist attacks in the next period. Thus, it validates my conclusion that terrorism follows a self-sustaining pattern. This causal relationship can be explained by the public attention paid to terrorist attacks. The deterring and overwhelming effect of terrorism encourages both the rational strategists administering their own agenda of terror and their imitators to carry out further attacks. Whereas the strategists are driven by the efforts of their recently conducted terrorist operations, their imitators get inspired by either the method of attack or the media feedback in the public perception (Lawson & Stedmon, 2015). Either way, this relationship describes an unsustainable trend with a declining leverage, which can be explained by the mechanism of the Recency Effect. Despite this insignificance in the long term, this discernment of a causal affiliation epitomizes one of the most important findings of my thesis. It proves that terror is endogenous to the used indicator variables of state fragility and moreover describes an endemic phenomenon expressing a partially self-sustaining pattern.

Furthermore, Model 7.1 also postulates coefficient estimates of indicators of fragility that have a decreasing impact on the numbers of terrorist attacks. Contrary to the positive relationship described before, my results show that a more unfavorable, thus higher score of *Human Flight and Brain Drain* ($p=.052$) and *External Interventions* ($p=.055$) reduce the total number of terrorist attacks. The *Human Flight and Brain Drain* variable measures the loss of intellectuals,

professionals, and political dissidents and accounts for voluntary emigration. A higher index score indicates that the brain drain of a country became chronic and sustained, which results in a significant decline of the professional and middle class of the country (Fund for Peace, 2014). This finding aligns with my results from the *Economic Inequality* variable that relates inequality such as a higher relative deprivation to an increase in terrorist attacks. An increase in the emigration of intellectuals reduces the magnitude of inequality and accordingly decreases the total number of terrorist attacks. It seems that both variables *Economic Inequality* and *Human Flight and Brain Drain* have adverse impacts on the dependent variable of my model. This might be an indicator for collinearity; though, given the data, it is impossible to determine the degree.

My coefficient estimates for the indicator variable *External Interventions* reveal another negative relationship between the explanatory variables of my model and my dependent variable. This indicator measures the extent of the full spectrum of means of external interventions (Fund for Peace, 2014). Relatively moderate types of intervention, indicated by lower scores, are economic interventions by external actors, including NGOs, development projects, and foreign aid. More powerful means of external interventions are military engagements such as covert or overt interventions, externally supported militia, and in its strongest form, peacekeeping missions. Given this design of the *External Interventions* variable, this indicator allows us to derive some interesting conclusions. It seems that weaker instruments of external power projection at least do not have a lessening effect or maybe even have an unfavorable effect on the number of terrorist attacks. This can be for several reasons. First of all, economic interventions as part of a foreign aid program are not specifically designed to counter terrorism but to improve a country's economy and consequently its humanitarian situation in the long term. The purpose of economic aid and associated cash flows is to ensure the subsistence level for the people, to provide minimal standards, and moreover to foster prosperity. Thus, if at all, this quality of external intervention does have an implicit intent to counter terroristic behavior. A

second reason for this unfavorable relationship between the *External Interventions* variable and terrorism can be the inefficient allocation and use of external aids. Roodman (2007) shows that “much aid is poorly used —or, like venture capital, is good bets gone bad” (p. 18). Also, Mascarenhas and Sandler (2014) hypothesize that “foreign aid inflows may elevate terrorists’ resources (p. 337), thereby increasing terror,” and find that lagged remittances in fact have a positive impact on terrorism (Mascarenhas & Sandler, 2014). This obvious allocation problem might have further implications for the factionalization of a country and could eventually lead to a higher magnitude of perceived inequality. Both results arising from this distribution problem are actually increasing the number of terrorist attacks.

In contrast to these moderate instruments’ increasing impact on the number of terrorist attacks, the more powerful means of external interventions do at least have a containing effect on terrorist activities. According to my findings, the projection of military force entails fewer terrorist attacks and consequently appears to be an appropriate tool to mitigate, but not eradicate, terrorism as the confidence interval of this variable, ranging from -197.36 to 1.97, remains predominantly negative. Thus, my results prove that these interventions of highest intensity are not suitable to straightforwardly serve a sound and sustainable counterterrorism strategy. Notwithstanding, indirectly they do, as these means also affect the numbers of terrorist attacks in the next period.

I conclude that regardless the scale of a military intervention, the presence of foreign military forces obviously affects terrorist behavior.

To prevent an unfavorable effect from collinearity between the *Factionalized Elites* and *Group Grievance* variables, I omitted the latter variable in this model. It is important to admit that a certain amount of collinearity remains between my different indicator variables. For this reason, the coefficient estimates always have to be interpreted in conjunction with the results from my raw data analysis in Model 6.

With respect to my previous recognition of irrelevant indicator variables, which are unsuitable to explain terrorism in a raw data analysis, I purposefully did not control for the *Economy* and *Refugees and IDPs* variables in my final Model 7.1, as the model does not improve from it. However, if I included them, they remained highly insignificant, which again supports my conclusion from Model 6 that economy and the influx of refugees have no causal implications for the number of terrorist attacks. Instead, their high level of insignificance indirectly refutes Choi and Salehyan, who claimed that a rising number of refugees leads to more terrorist activities (Choi & Salehyan, 2013). My finding holds in the short term; however, over time and subject to a society's capacity to assimilate and integrate refugees, this increasing influx might eventually lead to a higher extent of factionalization, which was shown to induce terrorist attacks.

In a guest lecture at the Heinrich Heine University of Dusseldorf, former Federal President of Germany Joachim Gauck, took a general position with regard to the long-term consequences of migration for a host country and its society. He elaborated that “a nation-state should not be overstrained. Anyone who imagines, as an imaginary representative of a world citizenship, taking away all borders of the nation-state, not only overburdens the material, territorial and social capacities of every state, but also the psychological capacities of its citizens. Even cosmopolitan people reach their limits when developments of a cultural nature are too fast and too extensive” (Tychis Einblick. Das liberal-konservative Meinungsmagazin [Tychi's insight. The liberal-conservative opinion magazine], 2018).² This statement reflects exactly the results of my analysis and puts emphasis on the role of social capacities to integrate refugees.

4. Model 7.2: Best Fitted Model—Logged Total Monetary Value and State Fragility (Arellano-Bond Estimator)

The results from my estimation of Model 7.2 are presented in Table 6.

² This speech was held in the German language. For the purpose of better understanding and moreover of putting emphasis on the message, I translated it into English language.

Table 6. Model 7.2

Model 7.2: Best Fitted Model - Logged Total Monetary Value and State Fragility (Arellano-Bond Estimator)

Incpyear	
L1.	0.222** [0.102]
Factionalized Elites	-0.457 [0.378]
Economic Inequality	-0.862** [0.344]
Human Flight and Brain Drain	0.269 [0.504]
Public Services	0.667 [0.676]
External Intervention	-0.237 [0.383]
State Legitimacy	0.206 [0.684]
Observations	390
Number of countries	72
N	390

*** p<0.01, ** p<0.05, * p<0.1

In my Model 7.2, two coefficient estimates, *Economic Inequality* ($p=.012$) and the first lag of the dependent variable ($p=.003$), prove to be statistically significant. Contrary to my previous results, I find that economic inequality is negatively related to the value of total damage. This contradictory finding should not be overstated, as Young finds that the coefficient estimates of explanatory variables might significantly vary across different operationalizations of terrorism (Young, 2016).

The lag of the dependent variable remains positive and proves the self-sustaining potential of terrorism once again, however, to a smaller extent. A further reason for the divergent outcomes of this model might be the fact that I did not discount my aggregate value of total damage to the NPV. Consequently, the direction and the magnitude of my coefficient estimates might be misleading.

Overall, I conclude that this model, using a different operationalization of terrorism, is less able to explain the relationship between indicators of state fragility and terrorism. Nevertheless, Model 7.2 is partially suitable to discern causality and to serve as a robustness check for my claim that economic inequality is a cause of terrorism and furthermore terrorism entails terrorism in the next period.

5. Model 7.3: Best Fitted Model—Total Number of Fatalities and State Fragility (Arellano-Bond Estimator)

The results from my estimation of Model 7.3 are presented in Table 7.

Table 7. Model 7.3

Model 7.3: Best Fitted Model - Total Number of Fatalities and State Fragility (Arellano-Bond Estimator)	
incperyear	
L1.	0.741*** [0.074]
L2.	-0.126** [0.054]
L3.	0.038 [0.075]
Factionalized Elites	459.582* [242.662]
L1.Factionalized Elites	-193.587 [246.377]
Economic Inequality	-553.289 [379.744]
L1.Economic Inequality	673.691 [441.434]
Human Flight and Brain Drain	-216.207 [247.261]
L1.Human Flight and Brain Drain	-35.39 [136.091]
Public Services	404.373 [523.349]
L1.Public Services	-451.103 [578.315]
External Intervention	-454.489 [402.523]
L1.External Intervention	240.357 [364.922]
State Legitimacy	85.206 [211.512]
L1.State Legitimacy	-240.232 [184.300]
Observations	1,185
Number of countries	173
N	1185

*** p<0.01, ** p<0.05, * p<0.1

In Model 7.3, I find the variable *Factionalized Elites* to be significant (p=.058) and positively related to my measure of terrorism. Again, the first lag of my dependent variable proves to be a good predictor of terrorism in the next period. Interestingly, in this model, also the second lag of my dependent variable is significant, but this time expressing a downward direction, reducing the total reciprocal effect by approximately 40% to a value of .615. This confirms my

previous findings of the self-sustaining potential of terrorism: however, these effects over the course of time appear to be more persistent. Though there is no significant sustainable trend observable, as the third lag of the dependent variable is highly insignificant. An explanation for this significance above the threshold of one period might be attributed to the design of my operationalization of terrorism, which counts fatalities. In this context, it appears possible that the sheer body counts do have a bigger leverage with respect to the self-sustaining potential of terrorism.

Consequently, I regard my Model 7.3 to be a partial validation of my Model 7.1, which expresses the robustness of my results.

C. COMPARING THE RESULTS FROM THE DIFFERENT MODELS

In this third and last step of my methodology, I compare the findings from my different models to draw some conclusions about the applicability and the robustness of my results. The models developed in this thesis have different purposes. Model 1 uses the NBR as the industry standard in the research field of finding determinants of terror and aims to reproduce Piazza's approach to investigate the fragility-terrorism nexus while taking advantage of the larger amount of data available today (Piazza, 2008). This model and its advancements are not designed to explicitly find causation. Their purpose is to consider whether the security concerns associated with fragile states (POTUS, 2017) are observable and verifiable in the data and therefore justify a further and more detailed investigation. The downside of this approach is that the NBR model does not account for the reverse causality bias stated before and therefore requires a thoughtful interpretation especially when it comes to communicating recommendations for policy makers.

Moreover, I introduced Model 5, a model designed to investigate a causal relationship between my indicator variables and the number of terrorist attacks and which furthermore explicitly addresses the problems arising from the endogeneity problem. However, this happens at the expense of a smaller statistical power, as

Model 5 uses parts of the data to create practicable and valid instruments from past levels to determine causality. Nevertheless, in comparison, this Model 5 and its advancements have a greater explanatory power and are more suitable to derive recommendations for counterterrorism strategies.

If, by comparison, all or at least some coefficient estimates of my different models are statistically significant and furthermore lead in the same direction, my Arellano-Bond Estimator Model allows one to conclude that the NBR is robust enough to withstand endogeneity and therefore provides valid and useful coefficient estimates. Consequently, the reverse causality bias in the fragility-terrorism nexus would become more or less negligible. As a result, after this validation, the more simplistic NBR model gets a higher connotation with respect to its usefulness and applicability, and furthermore takes advantage of coming along with higher statistical power.

In fact, the comparison of the coefficient estimates of numerous variations of Model 2 and Model 5 reveals that there was never conformity in terms of significance and direction of a variable's coefficient estimate at the same time. Oftentimes, my results from the NBR Model and my Arellano-Bond Estimator approach are even highly contradictory, which leads me to the conclusion that the count regression model is inappropriate to capture the effects of indicators of state fragility on the number of terrorist attacks sufficiently.

Additionally, the fact that a terrorist attack in period 1 entails between .68 up to .81 terrorist attacks in the next period illustrates the leverage of the endogeneity issue in the fragility-terrorism nexus. Hence, the problems arising from this reverse causality bias are simply too substantial to use the NBR as an appropriate model to derive strategies for policy makers. Accordingly, all findings of determinants of terror using this methodology have a limited information value and should be handled with caution. As this statistical model fails to capture the effect of terror being endogenous to terrorism, the results are biased and can be dilutive and sometimes even misleading. Using the example of my coefficient estimates for the indicator variable *Refugees and IDPs* in my Model 4, this

association implies that on average 5.2% more terrorist attacks occur with a one-unit increase of the index score, which would have serious implications for the European countries experiencing the migrant crisis that begun in 2015. However, the inclusion of the *Refugees and IDPs* variable in an Arellano-Bond Estimator approach proves to be highly insignificant and therefore leads to the conclusion that an influx of refugees does not lead to more terrorism. A second example relates to the estimates of my *Factionalized Elites*, *Human Flight and Brain Drain*, and *External Intervention* variables, which are highly insignificant in the NBR model but are found to have a significant causal implication for terrorism in Model 7.1. In contrast to this limited meaningfulness of the correlations from my Models 1 through 3, the Arellano-Bond Estimator approach is methodologically sound and suitable to draw conclusions about the causal relationship between some indicators of state fragility and the number of terrorist attacks, or rather, the scale of terror.

THIS PAGE INTENTIONALLY LEFT BLANK

VI. CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

A. CONCLUSIONS

With my first three models, I adopted Piazza's approach to investigate the relationship between state fragility and terrorism. For this analysis, I used the NBR, which is known to be the "standard model in the empirical analysis of terrorism" (Kis-Katos et al., 2012, p. 13). Knowing that this model is not suitable to treat my dependent variable to be endogenous to the number of terrorist attacks, I found a significant but economically weak negative relationship between state fragility and the incidence of terror. A raw data analysis in Model 2 validates this finding, which is contrary to Piazza (2008), who found evidence that "states experiencing intense state failures are statistically more likely to be the target of attacks and are more likely to have their nationals commit attacks overseas" (p. 481).

Nevertheless, in Model 4, I identified the two indicator variables *Public Services* and *Refugees and IDPs* to be positively associated with the number of terrorist attacks. I showed that despite the NBR's status as the 'industry standard,' it is an inappropriate model to derive causal implications from the relationship between my indicator variables and the number of terrorist attacks, because of the associated reverse causality bias.

In contrast, the Dynamic Panel Regression approach using the Arellano-Bond Estimator is methodologically sound and suitable to draw conclusions about the causal relationship between some indicators of state fragility and the number of terrorist attacks, or rather, the scale of terror.

Model 7.1 provides good arguments to develop recommendations for policies and programs as it identifies four indicators of state fragility that are causally related with the number of terrorist attacks. Moreover, my Model 7.2 and Model 7.3 partially validate the previous findings by using a different dependent variable to measure terrorism, thus making my findings more robust.

The significant causal effects of indicators of state fragility on terrorism show that inequality is an important root cause for terrorist attacks. The intensity of relative deprivation, economic inequality, and frustration over the unequal distribution of resources have inflammatory effects, which eventually lead to a higher incidence of terrorist activity; a finding that confirms the theory of relative deprivation introduced by Gurr (Gurr, 1970). Based on this result, it is reasonable to conclude that an increase of group-based inequality, whether perceived or an objective fact, drives a wedge between a society's groupings and has a catalytic effect on the progress of factionalization. An effective measure to prevent terrorism should therefore address this causal relationship and aim to reduce economic inequality along group lines. In this context, the economic principle of opportunity cost becomes a helpful instrument, as it allows policy makers to determine the despair of disadvantaged minorities and moreover helps to monitor and predict their violent potential.

A second root cause for the greater incidence of terrorist attacks is the rise of factionalized elites in a society. This indicator variable proves to be a good predictor for terrorism as I found a strong and significant underlying relationship between this explanatory variable and the number of terrorist attacks. Consequently, terror is an outcome of an endemic problem, which is inherent to a society and increases with the level of factionalization along ethnic and religious lines, and thereby proves the mechanism of revolutionary change introduced by Johnson (Johnson, 1982). Moreover, inequalities in access to political power can further accelerate this dynamic.

A strategy to mitigate these adverse dynamics is to intervene with the different factions in order to reestablish and moreover to maintain a state of relative equilibrium. However, subject to a society's cultural values, the instruments used in this process might vary as they are not universally applicable. Societies are not homogenous, which is why policies always have to be tailored to the mission; however, the span of available political instruments remains the same. Appropriate means to address the problems arising from factionalized elites include attaining

political reconciliation, inducing a burgeoning middle class to fill the gaps, controlling the concentration of wealth, and supervising the control of resources. Also creating a national identity can be a successful strategy to propitiate rival groupings.

Another implication drawn from my results relates to the average mix of instruments for external interventions portrayed by the FSI with food aid, development assistance, military exercise, military intervention, sanctions, and investment climate. This mix of instruments is not set up efficiently to prevent or counter terrorist attacks. As a matter of fact, my findings provide proof that a 'better' external intervention indicator, synonymous with a smaller index score, is actually increasing terrorist activities. My results show that the projection of military force entails fewer terrorist attacks and consequently appears to be an appropriate tool to mitigate, but not eradicate, terrorism as the confidence interval of this variable, ranging from 197.36 to 1.971088, remains predominantly negative. Accordingly, my results prove that these interventions of highest intensity are not suitable to straightforwardly serve a sound and sustainable counterterrorism strategy as they do not have an instantaneous lessening effect on the number of terrorist attacks. Notwithstanding, indirectly they do have an effect, as these means also affect the numbers of terrorist attacks in the next period, thus addressing terrorism's self-sustaining mechanism.

Additionally, an indirect but valuable outcome derived from my Arellano-Bond Estimator Models relates to the role of refugees. There is absolutely no evidence of a significant relationship between my *Refugees and IDPs* variable and terrorism, neither in my raw data analysis of Model 6 nor in any of my more advanced models. However, there might be implications in the long term, as a worsening of a country's refugee situation may converge with the problem of factionalization and inequality, which remains subject to a society's capacity to assimilate and integrate groups. This has implications for policy insofar as the underlying mechanism reveals a strict time-dependency, which might become troublesome only over time. Consequently, and seen from the strategic

perspective, an open border policy to give shelter to refugees cannot solely be justified by altruistic arguments. Despite the moral obligation to help refugees in need, such a policy must be accompanied by a set of instruments that contemporaneously increase a society's resilience and capacity to assimilate and integrate refugees with a different cultural background. The solution to the problem lies in a sustainable and future-oriented handling of migration movements, and the strategic toolset should include the consideration of and the potential to implement a closed-border-policy to strengthen the resilience of the state and reduce its susceptibility for violent outbreaks.

At the end, my proof that terror is certainly endogenous shows that terrorism creates a momentum, which has an instantaneous effect on the prospective dynamics of terrorism. The fact that a terrorist attack in period one entails between .68 up to .81 terrorist attacks in the next period illustrates the enormous leverage of this momentum. The relatively small range of all significant values for the coefficient estimates of my lagged dependent variable, subject to the different models, demonstrates the robustness of my outcomes. Compared to my other identified root causes for terrorism, this predictor has by far the biggest impact on terrorism as it follows a morbid self-sustaining pattern.

Consequently, I like to emphasize the importance to counter terrorist activities immediately and rigorously. An early intervention with effective effort, therefore, has the potential to significantly decrease the number of future terrorist attacks. Furthermore, my findings reinforce the argument that a comprehensive and holistic national security strategy to reduce terrorist activities should address the problems arising from state fragility, however not per se, but with respect to relative deprivation and factionalization along ethnic and religious lines. Knowing about these root causes helps decision makers to spend the generally limited resources in the fight against terrorism more efficiently.

B. RECOMMENDATIONS FOR FUTURE RESEARCH

For future research, I recommend the replication of my results and a more detailed analysis with respect to the causal impacts of external interventions on state fragility. In view of the aforementioned, it will be relevant to investigate the respective causal effects of the sub-indicators, which are jointly evaluated in my *External Intervention* indicator variable. With the data provided by the FSI, it is impossible to determine the degree of collinearity between the *External Intervention* variable and inequalities arising from an inefficient use of foreign aid over time.

The same logic applies to the effects of the influx of refugees, subject to the society's capacity to assimilate groups in the long term. Further research is needed to investigate the time dependencies between terrorism and migration movements.

Furthermore, terrorism is not a homogeneous phenomenon although it is predominantly treated that way in this thesis. Consequently, for future research I recommend an analysis with the focus on the difference between domestic and transnational terrorism. Moreover, my presumption that the incidence of terrorism does not follow a strictly linear pattern should be subject to further investigations.

Finally, it is also important to pick up on Young's recommendation to operationalize terrorism differently (Young, 2016). With respect to my *totalvalue* variable, it would be interesting to compare results, once this variable is further refined and discounted for the NPV.

THIS PAGE INTENTIONALLY LEFT BLANK

APPENDIX A. LIST OF SUB-INDICATORS IN THE FSI

Indicator: Demographic Pressures	Disasters
	Disease
	Food and Nutritional Scarcity
	Water Scarcity
	Environment
	Age Distribution
	Arable Land
	Population Growth
	Mortality/Life Expectancy
Indicator: Refugees/IDPs	Refugees (Country of Asylum/Absorption)
	Refugees (Country of Origin)
	IDPs (Country of Residence)
	Refugee Camps/Complex Humanitarian Emergencies
Indicator: Group Grievance	Ethnic Discrimination/Exclusion
	Ethnic/Communal Clashes
	Sectarian/Religious Clashes
	Religious Persecution
Indicator: Human Flight	Physicians per capita
	Net Migration
Indicator: Uneven Development	Income Inequality
	Urban/Rural Divide
	Poverty
Indicator: Economy/Poverty	Budget Balance
	Unemployment
	Economic Growth
	Inflation
	Poverty
	Foreign Direct Investment
	Productivity
	Illicit Economy
Indicator: State Legitimacy	Representative Governance
	Corruption
	Civil/Political Liberties
	Illicit Economy
	Political Prisoners
	Power Transition

	Riots/Protests
Indicator: Public Services	Policing
	Education
	Healthcare
	Internet and Communications
	Water and Sanitation
	Electricity and Power
Indicator: Human Rights	Political Terror/Homicidal Violence
	Gender Equality/Representation
	Civil/Political Liberties
	Human Trafficking
	Religious Persecution
	Torture and Executions
Indicator: Security Apparatus	Torture and Executions
	Coup/Mutiny
	Bombing/Attack
	Political Prisoners
	Rebels and Militants
	Battle Related Deaths
	Terrorism
	Crimes/Homicides
Indicator: Factionalized Elites	Coup/Mutiny
	Defectors
	Power Transition
Indicator: External Intervention	Food Aid/Development Assistance
	Military Exercises
	Military Intervention
	Sanctions
	Investment Climate

(J. J. Messner, email to author, November 17, 2017)

APPENDIX B. MODEL 2: RAW DATA ANALYSIS—NUMBER OF TERRORIST ATTACKS AND STATE FRAGILITY

Model 2: Raw Data Analysis - Number of Terrorist Attacks and State Fragility (FE NBR)												
incperyear	[.]	[.]	[.]	[.]	[.]	[.]	[.]	[.]	[.]	[.]	[.]	[.]
Security Apparatus	0.983 [0.015]											
Factionalized Elites	0.938*** [0.015]											
Group Grievance		0.927*** [0.018]										
Economy			0.994 [0.018]									
Economic Inequality				0.832*** [0.019]								
Human Flight and Brain Drain					0.953*** [0.018]							
State Legitimacy						0.914*** [0.016]						
Public Services							0.991 [0.016]					
Human Rights								0.909*** [0.016]				
Demographic Pressures									0.919*** [0.017]			
Refugees and IDPs										0.971* [0.015]		
External Intervention											0.978 [0.017]	
Observations	1,871	1,871	1,871	1,871	1,871	1,871	1,871	1,871	1,871	1,871	1,871	1,871
Number of countries	173	173	173	173	173	173	173	173	173	173	173	173
N	1871	1871	1871	1871	1871	1871	1871	1871	1871	1871	1871	1871

*** p<0.01, ** p<0.05, * p<0.1

Coefficient estimates reported in Incident Rate Ratios (IRR)

THIS PAGE INTENTIONALLY LEFT BLANK

APPENDIX C. MODEL 6: RAW DATA ANALYSIS—NUMBER OF TERRORIST ATTACKS AND STATE FRAGILITY (ARELLANO- BOND ESTIMATOR)

Model 6: Raw Data Analysis - Number of Terrorist Attacks and State Fragility (Arellano-Bond Estimator)											
incperyear											
L1.	0.781***	0.759***	0.831***	0.799***	0.807***	0.770***	0.791***	0.863***	0.786***	0.794***	0.788***
	[0.129]	[0.136]	[0.150]	[0.164]	[0.182]	[0.137]	[0.103]	[0.162]	[0.118]	[0.117]	[0.090]
L2.	-	-	-	-	-	-	-	-	-	-	-0.009
											[0.143]
Factional- ized Elites	34.086										
	[25.766]										
Group Grievance		55.056**									
		[27.998]									
Economy			-2.747								
			[6.360]								
Economic Inequality				-6.369*							
				[3.836]							
Human Flight and Brain Drain					-52.916**						
					[26.870]						
State Legitimacy						-102.25					
						[63.602]					
Public Services							-52.477				
							[42.131]				
Human Rights								-77.19			
								[54.229]			
Demograp hic Pressures									-14.715		
									[12.211]		
Refugees and IDPs										-4.005	
										[19.608]	
External Intervention											-153.452**
											[75.486]
Observa- tions	1,531	1,531	1,531	1,531	1,531	1,531	1,531	1,531	1,531	1,531	1,358
Number of countries	173	173	173	173	173	173	173	173	173	173	173
N	1531	1531	1531	1531	1531	1531	1531	1531	1531	1531	1358

*** p<0.01, ** p<0.05, * p<0.1

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF REFERENCES

- Arellano M., & Bond S. (1991). Some tests of specification for panel data: Monte Carlo evidence and application to employment equations. *Review of Economic Studies*, 58(2), 277–297. Retrieved from <http://www.jstor.org/stable/2297968>
- Blomberg, S. B., Gaibullov, K., & Sandler, T. (2011). Terrorist group survival: Ideology, tactics, and base of operations. *Public Choice*, 149(3/4), 441–463. Retrieved from <https://www.jstor.org/stable/pdf/41483745.pdf>
- Caplan, B. (2006). Terrorism: The relevance of the rational choice model. *Public Choice* 128, 91–107. Retrieved from <http://www.springerlink.com/index/pdf/10.1007/s11127-006-9046-8>
- Caruso, R., & Schneider, F. (2010). The socio-economic determinants of terrorism and political violence in Western Europe (1994–2007). *Università Cattolica del Sacro Cuore di Milano, Institute of Economic Policy/CSEA*, 1–26.
- Choi, S. W., & Salehyan, I. (2013). No good deed goes unpunished: Refugees, humanitarian aid, and terrorism. *Conflict Management and Peace Science*, 30(1), 53–75. Retrieved from <http://journals.sagepub.com/doi/pdf/10.1177/0022002713515403>
- Coggins, B. L. (2015). Does state failure cause terrorism? An empirical analysis (1999–2008). *Journal of Conflict Resolution*, 59(3), 455–483. Retrieved from <http://doi.org/10.1177/0022002713515403>
- Dahrendorf, Ralf (1959). *Class and class conflict in industrial society*. Redwood City, CA: Stanford University Press.
- Director of National Intelligence. (2009, Aug.). *National intelligence strategy 2009*. Washington, DC. Retrieved from <https://fas.org/irp/offdocs/nis2009.pdf>
- Drakos, K., & Gofas, A. (2016). The devil you know but are afraid to face. *Journal of Conflict Resolution*, 50(5), 714–735. Retrieved from <http://doi.org/10.1177/0022002706291051>
- Findley, M. G., & Young, J. K. (2011). Terrorism, democracy, and credible commitments. *International Studies Quarterly*, 55(2), 357–378. Retrieved from <http://doi.org/10.1111/j.1468-2478.2011.00647.x>

- Freytag, A., Krueger, J. J., Meierrieks, D., & Schneider, F. (2011). The origins of terrorism: Cross-country estimates of socio-economic determinants of terrorism. *Jena Economic Research Papers 2009* (009), 1–22. Retrieved from https://www.researchgate.net/publication/23970157_The_Origins_of_Terrorism_-_Cross-Country_Estimates_on_Socio-Economic_Determinants_of_Terrorism
- Fund for Peace (2017). *Fragile States Index* [Database]. Retrieved from <http://fundforpeace.org/fsi/>
- Gassebner, M., & Luechinger, S. (2011). Lock, stock, and barrel—A comprehensive assessment of the determinants of terror. *Public Choice*, 149, 235–261. Retrieved from <http://www.jstor.org/stable/41483735>
- George, J. (2016). State failure and transnational terrorism. *Journal of Conflict Resolution*, 96(2), 1–25. Retrieved from <http://doi.org/10.1177/0022002716660587>
- Gurr, T. R. (1970). *Why men rebel*. Princeton, NJ: Princeton University Press.
- Haims, M.C., Gompert, D.C., Treverton, G.F., & Stearns, B.K. (2008). *Breaking the failed-state cycle*. Santa Monica, CA: RAND Corporation. Retrieved from https://www.rand.org/content/dam/rand/pubs/occasional_papers/2008/RAND_OP204.pdf
- Hagel, C. (2004). A republican foreign policy. *Foreign Affairs* 83(4), 64–76. Retrieved from http://www.kas.de/upload/dokumente/trans_portal/hagel-artikel.pdf
- Hehir, A. (2007). The myth of the failed state and the war on terror: A challenge to the conventional wisdom. *Journal of Intervention and Statebuilding*, 1(3), 307–332. Retrieved from <http://doi.org/10.1080/17502970701592256>
- Johnson, C., 1982. *Revolutionary change*. Redwood City, CA: Stanford University Press.
- Kang, S. J., & Lee, H. S. (2005). Terrorism and FDI flows: Cross-country Dynamic Panel Estimation. *Journal of Economic Theory and Econometrics* 18(1), 1–17. Retrieved from <http://es.re.kr/eng/upload/jetem18-1-3.pdf>
- Kis-Katos, K., Liebert, H., & Schulze, G. (2012). On the heterogeneity of terror. *European Economic Review* 68, 1–45. Retrieved from <http://doi.org/10.1016/j.euroecorev.2014.02.009>

- Krieger, T., & Meierrieks, D. (2011). What causes terrorism? *Public Choice*, 147(1–2), 3–27. Retrieved from <http://doi.org/10.1007/s11127-010-9601-1>
- . (2015). Does income inequality lead to terrorism? Evidence from the post-9/11 era. *SSRN Electronic Journal*, 1–30. Retrieved from <http://doi.org/10.2139/ssrn.1647178>
- Krueger, A. B. (2007). *What Makes a Terrorist—Economics and the roots of terrorism*. Princeton, NJ: Princeton University Press.
- Lawson, G., and Stedmon, A. (2015). *Hostile intent and counter-terrorism: human factors theory and application*. Burlington, VT: Ashgate.
- Llussá, F., & Tavares, J. (2011). The economics of terrorism: A (simple) taxonomy of the literature. *Defense and Peace Economics*, 22(2), 105–123. Retrieved from <http://doi.org/10.1080/10242694.2011.542331>
- Mansfield, E. D., & Snyder, J. (1995). Democratization and the danger of war. *International Security*, 20(1), 5–38. Retrieved from <http://doi.org/10.2307/2539213>
- Mascarenhas, R., & Sandler, T. (2014). Remittances and terrorism: A global analysis. *Defense and Peace Economics*, 25(4), 331–347. Retrieved from <http://www.tandfonline.com/doi/pdf/10.1080/10242694.2013.824676?needAccess=true>
- Meierrieks, D., & Gries, T. (2013). Causality between terrorism and economic growth. *Journal of Peace Research*, 50(1), 91–104. Retrieved from <http://doi.org/10.1177/0022343312445650>
- National Consortium for the Study of Terrorism and Responses to Terrorism (START). *Global terrorism database (GTD)* [Database]. Retrieved October 23, 2017 from <http://www.start.umd.edu/gtd/using-gtd/>
- Newman, E. (2007). Weak states, state failure, and terrorism. *Terrorism and Political Violence*, 19(4), 463–488. Retrieved from <http://doi.org/10.1080/09546550701590636>
- Okafor, G., & Piesse, J. (2017). Empirical investigation into the determinants of terrorism: Evidence from fragile states. *Defense and Peace Economics*, 2(5), 1–15. Retrieved from <http://doi.org/10.1080/10242694.2017.1289746>
- Pape, R. A. (2017). The strategic logic of suicide terrorism. *The American Political Science Review*, 97(3), 343–361. Retrieved from <http://www.jstor.org/stable/3117613>

- Piazza, J. A. (2008). Incubators of terror: Do failed and failing states promote transnational terrorism? *International Studies Quarterly*, 52(3), 469–488. Retrieved from <http://doi.org/10.1111/j.1468-2478.2008.00511.x>
- President of the United States of America. (2018). *National security strategy*, 1–35. Retrieved from <https://www.whitehouse.gov/wp-content/uploads/2017/12/NSS-Final-12-18-2017-0905.pdf>
- Randahl, D. (2016). Refugees and terrorism. *PAX et Bellum Journal* 3(1): 103–129. Retrieved from <http://paxetbellum.org/wp-content/uploads/2015/11/Pax-et-Bellum-Journal-Third-Edition-Spring-2016.pdf>
- Rice, Condoleezza. (2006, January). Transformational diplomacy. Presented at Georgetown University. Retrieved from <https://2001-2009.state.gov/secretary/rm/2006/59306.htm>
- Rohlf, C. & Sullivan, R. (2013). The cost-effectiveness of armored tactical wheeled vehicles for overseas U.S. Army operations. *Defense and Peace Economics*, 24 (4), 293–316. Retrieved from <https://doi.org/10.1080/10242694.2012.723158>
- Roodman, D. (2007). The anarchy of numbers: Aid, development, and cross-country empirics. *Center for Global Development*, 32, 1–42. Retrieved from https://www.cgdev.org/files/2745_file_The_Anarchy_of_Numbers_final.pdf
- Sandler, T. (2013). Introduction: Advances in the study of the economics of terrorism. *Southern Economic Journal*, 79(4), 768–773. Retrieved from <http://doi.org/10.4284/0038-4038-2013.007>
- . (2014). The analytical study of terrorism: Taking stock. *Journal of Peace Research*, 51(2), 257–271. Retrieved from <http://doi.org/10.1177/0022343313491277>
- Schulz, N. (2015). Dangerous demographics? The effect of urbanization and metropolization on African civil wars, 1961–2010. *Civil Wars*, 17(3), 291–317. Retrieved from <https://doi.org/10.1080/13698249.2015.1100277>
- Tychis Einblick. Das liberal-konservative Meinungsmagazin [Tychi's insight. The liberal-conservative opinion magazine]. (2018). Retrieved and translated from <https://www.tichyseinblick.de/daily-es-sentials/joachim-gauck-mich-erschreckt-der-multikulturalismus/>
- Tikuisis, P. (2009). On the relationship between weak states and terrorism. *Behavioral Sciences of Terrorism and Political Aggression*, 1(1), 66–79. Retrieved from <http://doi.org/10.1080/19434470802482175>

Young, J. K. (2016). Measuring terrorism. *Terrorism and Political Violence*, 1–23.
Retrieved from <http://doi.org/10.1080/09546553.2016.1228630>

THIS PAGE INTENTIONALLY LEFT BLANK

INITIAL DISTRIBUTION LIST

1. Defense Technical Information Center
Ft. Belvoir, Virginia
2. Dudley Knox Library
Naval Postgraduate School
Monterey, California